MINISTRY OF EDUCATION AND SCIENCE OF UKRAINE

NATIONAL AVIATION UNIVERSITY

Faculty of Aeronavigation, Electronics and Telecommunications

Department of computer integrated complexes

ADMIT TO DEFENSE

Head of the graduating department

__________ Viktor M. Sineglazov

“_____”_________________2024y.

QUALIFICATION WORK

(EXPLANATORY NOTE)

OF THE GRADUATE OF THE EDUCATIONAL DEGREE

“BACHELOR”

Specialty 151 "Automation and computer-integrated systems"

Educational and professional program "Computer-integrated technological processes and production"

Theme: An intelligent system for predicting the need to replace aircraft parts based on transformers

Performer: student of FAET-323 group Andrii Dziuba

Supervisor: Vladyslav HORBATYUK

Norm controller: ___________ Filyashkin M.K.

Kyiv – 2024

МІНІСТЕРСТВО ОСВІТИ І НАУКИ УКРАЇНИ

НАЦІОНАЛЬНИЙ АВІАЦІЙНИЙ УНІВЕРСИТЕТ

Факультет аеронавігації, електроніки та телекомунікацій

Кафедра авіаційних комп'ютерно-інтегрованих комплексів

ДОПУСТИТИ ДО ЗАХИСТУ

Завідувач випускової кафедри

______ Віктор СИНЄГЛАЗОВ

“____” ______________2024 р.

КВАЛІФІКАЦІЙНА РОБОТА

(ПОЯСНЮВАЛЬНА ЗАПИСКА)

ВИПУСКНИКА ОСВІТНЬОГО СТУПЕНЯ

“БАКАЛАВР”

Спеціалність 151 "Автоматизація, та комп’ютерно-інтегровані системи"

Освітньо-професійна програма "Комп’ютерно-інтегровані технологічні процеси і виробництва"

Тема: Інтелектуальна система прогнозування потреби заміни авіаційних деталей на основі трансформерів

Виконавець: студент групи ІК-323Ба Дзюба Андрій Олегович

Керівник: кандидат технічних наук Горбатюк Владислав Сергійович

Нормоконтроллер: ___________ Філяшкін М.К.

Київ – 2024

NATIONAL AVIATION UNIVERSITY
Faculty of Aeronautics, Electronics and Telecommunications
Department of aviation computer-integrated complexes

Bachelor's degree in education

Specialty151 “Automation and computer-integrated technologies”

APPROVED BY

Head of the department

_______________ Viktor M. Sineglazov

«_____»__________________2024 р.

TASKS

for the qualification work

DZIUBA Andrii

1. The topic of the qualification work is “An intelligent system for predicting the need to replace aircraft parts based on transformers”**.**

2.Term of work: from April 15, 2024 to June 16, 2024.

3. Initial data for the work: "Time Series Analysis and Its Applications" by Robert H. Shumway and David S. Stoffer (2017)

4.Contents of the explanatory note: 1) Review and analysis of intelligent forecasting systems; 2) Overview of transformers and their structure; 3) Overview and selection of databases; 4) Statement of the problem; 5) Database connection; 6) An example of a program for an intelligent system for predicting the need to replace aircraft parts based on transformers; 7) Analysis of the results.

5. List of required graphic (illustrative) material: Presentation in MicrosoftPowerPoint.

6. Calendar plan-schedule

№ cf.	Tasks.	The term fulfillment	A note on the execution
1	Familiarization with the task statement of the qualification work.	01.04.2024-04.04.2024	Done
2	Analysis of intelligent systems.	05.04.2024-24.04.2024	Done
3	Overview and analysis types of transformers and their application.	25.04.2024-1.05.2024	Done
4	Description of the fundamentals of machine learning.	2.05.2024-10.05.2024	Done
5	Overview and analysis batabase selection.	11.05.2024-25.05.2024	Done
6	Task statement.	26.05.2024-09.06.2024	Done
7	System data bases development.	1.06.2024-07.06.2024	Done
8	Preparation of an explanatory note, graphic materials, and a presentation for the thesis project.	07.06.2024-10.06.2024	Done
9	Submission of qualification work for defense	16.06.2024	Done

7. Date of the task issue: “ 15 " April 2024 p.

Thesis supervisor ______________ Horbatyuk V.S.

The task was accepted for execution ________________ Dziuba A.O.

НАЦІОНАЛЬНИЙ АВІАЦІЙНИЙ УНІВЕРСИТЕТ
Факультет аеронавігації, електроніки та телекомунікацій
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Освітньо-кваліфікаційний рівень бакалавр
Спеціальність151 «Автоматизація та комп’ютерно-інтегровані технології»

ЗАТВЕРДЖУЮ
Завідувач кафедри
_____________ Віктор СИНЄГЛАЗОВ
«____»________________2024 р.

ЗАВДАННЯ
на виконання кваліфікаційної роботи
ДЗЮБИ Андрія Олеговича

1. Тема кваліфікаційної роботи **«**Інтелектуальна система прогнозування потреби заміни авіаційних деталей на основі трансформерів ».

2.Термін виконання роботи: з 15 квітня 2024р. по 16 червня 2024 р.

3. Вихідні дані до роботи: "Time Series Analysis and Its Applications" by Robert H. Shumway and David S. Stoffer (2017)

4.Зміст пояснювальної записки: 1) Огляд та аналіз інтелектуальних систем прогнозування; 2) Огляд трансформерів та їх структури; 3) Огляд та вибір баз даних; 4) Постановка проблеми; 5) Підключення бази даних; 6) Приклад програми для інтелектуальної системи прогнозування потреби заміни авіа-деталей на основі трансформерів; 7) Аналіз результатів.

5. **Перелік обов’язкового графічного (ілюстративного) матеріалу:** Презентація в MicrosoftPowerPoint.

6. **Календарний план-графік**

№ пор.	Завдання	Термін виконання	Відмітка про виконання
1	Ознайомлення з постановкою задачі кваліфікаційної роботи.	01.04.2024-04.04.2024	Виконано
2	Аналіз інтелектуальних систем.	05.04.2024-24.04.2024	Виконано
3	Огляд і аналіз типів трансформерів та їх застосування.	25.04.2024-1.05.2024	Виконано
4	Опис основ машинного навчання.	2.05.2024-10.05.2024	Виконано
5	Огляд і аналіз вибору бази даних.	11.05.2024-25.05.2024	Виконано
6	Постановка завдання.	26.05.2024-09.06.2024	Виконано
7	Розробка системних баз даних.	10.06.2024-12.06.2024	Виконано
8	Оформлення пояснювальної записки, графічних матеріалів та презентації до дипломного проекту.	13.06.2024-19.06.2024	Виконано
9	Подання кваліфікаційної роботи до захисту	16.06.2024	Виконано

7. Дата видачі завдання: “ 15 "_ квітня 2024 р.

Керівник дипломної роботи ______________ Горбатюк В.С.

(підпис керівника) (П.І.Б.)

Завдання прийняв до виконання ________________ Дзюба А.О.

(П.І.Б.)

РЕФЕРАТ

Пояснювальна записка до кваліфікаційної роботи «Інтелектуальна система прогнозування потреби заміни авіа-деталей на основі трансформерів». Кваліфікаційна робота складається зі вступу, трьох розділів, загальних висновків, списку використаних джерел і має 50 сторінок, 9 малюнків, 2 формули, 3 тадлиці, 33 літературних джерел.

Мета дипломного проекту: Метою даного проекту є дослідження існуючих методів прогнозування з використанням інтелектуальних систем на основі трансформерів, а також побудова керованої моделі прогнозування потреби заміни авіа-деталей.

Основні завдання: Розробка та успішне навчання моделі для задач прогнозування потреби заміни авіа-деталей по існуючим історичним даним на основі мови програмування Python ми будемо використовувати базу даних PostgreSQL з використанням Python, використовувати бібліотеку psycopg2 і torch transformers pandas scikit-learn

Суть проекту: Дослідження існуючих методів прогнозування з використанням інтелектуальних систем обробки даних. Використання вже вивчених технологій побудови моделі для вирішення задач прогнозування потреби заміни авіадеталей на основі трансформерів.

Основні показники та результати: Прогнозування потреби заміни авіа-деталей давно привертає увагу фахівців у галузі авіації. Метою проекту є пошук та аналіз існуючих методів прогнозування потреби заміни авіа-деталей за допомогою інтелектуальних систем обробки даних на основі трансформерів. Розроблено просту модель прогнозування на основі мови програмування Python та бібілотеки psycopg2 призначеної для прогнозування потреби заміни авіа-деталей на основі трансформерів.

ABSTRACT

Explanatory note to the qualification work "Intelligent system for forecasting the needs of replacing aircraft parts based on transformers". The qualification work consists of an introduction, three chapters, general conclusions, a list of used sources and contains 50 pages, 9 figures, 2 formulas, 3 tables, 33 literary sources.

Metadiploma project: The method of this project is the study of existing methods of forecasting using intelligent systems based on transformers, as well as the built controlled model of forecasting the needs of replacing aircraft parts.

The main task: Development and successful training of models for the task of predicting the needs of replacing aircraft parts with existing historical data based on the Python programming language, we will use the PostgreSQL database using Python, using the psycopg2 library and torch transformers pandas scikit-learn

The essence of the project: Research of existing forecasting methods using intelligent data processing systems. The use of already studied technologies of model construction to solve the tasks of forecasting the needs of replacing aircraft parts based on transformers.

Key indicators and results: The forecast of the need to replace aircraft parts has long attracted the attention of specialists in the field of aviation. The method of the project is the search and analysis of existing methods of forecasting the need for replacement of aircraft parts using intelligent data processing systems based on transformers. A simple forecasting model based on the Python programming language and the psycopg2 library was developed, designed for the needs of forecasting the replacement of aircraft parts based on transformers.

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INTRODUCTION

The aviation sector, recognized for its stringent safety standards and substantial operational costs, relies heavily on efficient and precise maintenance protocols. An integral aspect of aviation maintenance involves timely part replacements to uphold aircraft safety and dependability. Historically, maintenance timetables have relied on fixed intervals or reactive strategies, often leading to premature replacements or unforeseen part malfunctions. Enhancing the efficiency and precision of maintenance operations necessitates the development of intelligent predictive systems.

This study centers on crafting and implementing an intelligent framework for anticipating aviation part replacements through transformer models. Transformers, a sophisticated class of deep learning models celebrated for their exceptional performance in natural language processing, have recently demonstrated significant potential in diverse predictive assignments. Leveraging transformers, this study strives to establish an advanced predictive maintenance system adept at precisely forecasting optimal part replacement timings.

The proposed system is tailored to scrutinize extensive operational and sensor data from aircraft, identifying pre-failure patterns and irregularities. By foreseeing part replacement probabilities and schedules, the system can aid airlines and maintenance crews in refining their maintenance calendars, curtailing downtime, and curbing expenses. Furthermore, this methodology aligns with the industry's progression towards predictive maintenance, emphasizing data-centric decision-making to enhance operational efficiency and safety.

CHAPTER 1
RESEARCH OF THE TOPIC

Transformers are a powerful tool for creating intelligent forecasting systems. Their ability to process large amounts of data and detect complex patterns makes them indispensable in many fields. However, to fully reveal the potential of transformers, it is necessary to continue research and improvement of these models.

1.1. Pertinence of the subject.

An shrewdly system for anticipating the ought to supplant flying parts based on transformers.

The flying industry is one of the foremost innovatively progressed and basically imperative circles of action, where security and unwavering quality are the most focal points. Upkeep of flying machine components plays a key part in guaranteeing flight security and operational efficiency. Customarily, upkeep of airplane components has been set up at foreordained interims or based on cycles of utilize[1]. This approach encompasses a number of disadvantages, such as untimely substitution of corrupted parts driving to pointless costs, or late substitution that will compromise flight security.

The significance of the think about is to a great extent critical components that influence the advanced flying industry:

2. Developing prerequisites for security and unwavering quality.

A tall level of security is the most necessity within the flying industry. in spite of strict directions and assessments, startling component disappointments still happen and can lead to genuine occurrences or mischances. An shrewdly determining framework competent of precisely foreseeing the require for substitution of parts essentially increments the unwavering quality of airplane, guaranteeing opportune support and minimizing the hazard of disappointment in basic conditions.

2. Financial efficiency.

The taken a toll of support and substitution of parts is one of the foremost noteworthy costs of flying companies. Conventional strategies based on settled interims or times of utilize regularly lead to untimely substitutions, squandering save parts and repair work. The utilize of prescient models based on transformers permits for fine-tuning the ideal time to supplant parts, coming about in noteworthy diminishments in support costs and expanded flying machine uptime.

3. Innovative progresses within the field of counterfeit insights.

The quick improvement of machine learning strategies, in specific transformers, opens up awesome unused openings for preparing and analyzing volumes of information. Transformers, initially created for characteristic dialect handling, have demonstrated successful in time arrangement determining and complex information handling, making them a promising apparatus for prescient upkeep. The use of such technologies will permit the investigation of tremendous clusters of information collected from sensors and upkeep logs to more precisely anticipate the condition of parts.

4. Competitive points of interest.

Flying companies that implement inventive support frameworks keep up competitive preferences within the showcase. Moving forward operational proficiency, diminishing upkeep costs and giving high-quality benefit makes strides the company's notoriety and increments client dependability. In expansion, such companies can adjust more quickly to modern administrative prerequisites and innovative changes that occur within the industry.

5. Natural maintainability

Optimizing support forms as well as diminishing the affect on the environment. Diminishing the number of untimely substitutions and more judicious utilize of assets leads to a lessening within the sum of squander and emissions associated with the production of modern components. Typically especially important within the setting of developing natural necessities and the crave to diminish the carbon footprint of the flying industry.

Result

The improvement and execution of an shrewdly framework for determining the needs of supplanting flying machine parts based on transformers is an pressing and imperative errand. It can altogether move forward flight safety, decrease maintenance costs, increment the competitiveness of flying companies and contribute to the natural supportability of the industry. The utilize of advanced strategies of fake insights and machine learning opens up unused skylines for improving upkeep and guaranteeing continuous operation of flying frameworks.

1.2. Data Acquisition

The total dataset is built utilizing flight recordings from the NGAFID database and upkeep records from MaintNet[2]. Each upkeep record portrays the sort of support performed on an airplane and the time period when support happened. From this data, we extricate that aircraft's flights happening some time recently and after the support period. As it were the primary 5 flights some time recently and after and any flights amid upkeep are extricated. All upkeep exercises were impromptu and done on ask. In any case, when issues are identified, FAA arrangement precludes the plane from flying. This implies that issues are continuously recognized at some point amid or after the primary flight some time recently upkeep. Each flight record contains readings from 23 diverse sensors each moment. A portrayal of the sensors can be found in Table 1. All flight information recordings come from the same air ship show, the Cessna 172.

The NGAFID serves as a store for common flying flight information, with a web entry for seeing and following flight security occasions for person pilots as well as for armadas of air ship Karboviak et al. (2018). The NGAFID right now contains over 900,000 hours of flight information created by over 780,000 flights by 12 distinctive sorts of airplane, given by 65 armadas and person clients, coming about in over 3.15 billion per moment flight information records over 103 potential flight information recorder parameters[3]. Five a long time of literary support records from a armada which given information to the NGAFID have been clustered by support issue type and after that approved by space specialists for the MaintNet venture, see Akhbardeh et al. (2020).

Table 1

Description of the data collected by aircraft sensors

Column Name	Description
volt1	Main electrical system bus voltage (alternators and main battery)
volt2	Essential bus (standby battery) bus voltage
amp1	Ammeter on the main battery (+ charging, - discharging)
amp2	Ammeter on the standby battery (+ charging, - discharging)
FQtyL	Fuel quantity left
FQtyR	Fuel quantity right

E1 FFlow	Engine fuel flow rate
E1 OilT	Engine oil temperature
E1 OilP	Engine oil pressure
E1 RPM	Engine rotations per minute
E1 CHT1	1th cylinder head temperature
E1 CHT2	2th cylinder head temperature
E1 CHT3	3th cylinder head temperature
E1 CHT4	4th cylinder head temperature
E1 EGT1	1st Exhaust gas temperature
E1 EGT2	2nd Exhaust gas temperature
E1 EGT3	3rd Exhaust gas temperature
E1 EGT4	4th Exhaust gas temperature
OAT	Outside air temperature
IAS	Indicated air speed
VSpd	Vertical speed
NormAc	Normal acceleration
AltMSL	Altitude miles above sea level

MaintNet's upkeep record logbook information was clustered into 36 distinctive upkeep issue sorts. The number of flights per issue sort is found in table 3 in Reference section A. In spite of the fact that a few support issues happen exceptionally once in a while, all upkeep issues with flight information are included within the full dataset. It is vital to note that the NGAFID collects genuine flight information from airplane flying with possibly flawed parts (as is the case for any genuine world armada of airplane). Usually since person components may fall flat without causing disastrous disappointment of the flying machine amid standard operation. The collection of this data poses no additional safety risk to the pilots because data collection occurs for all flights performed. For profound learning strategies, well performing MTS classifiers tend to utilize a few combination of Repetitive Neural Organize (RNN) and Convolutional Neural Organize (CNN) strategies, Karim et al. (2017), or CNN as it were strategies Wang et al. (2017).

1.3. Intelligent system and transformers.

Intelligent forecasting systems are several tools in many industries, including finance, medicine, logistics, and others. One of the most promising approaches to creating such systems is the use of transformers, a neural network architecture that was first introduced in 2017 for natural language processing tasks, but later found application in various areas of prediction[4].

An intelligent system is a software or hardware solution capable of performing complex tasks that normally require human intelligence. It uses a variety of artificial intelligence (AI) techniques, such as machine learning (ML), natural language processing (NLP), expert systems, neural networks, and other technologies for data analysis, decision making, pattern recognition, prediction, and process automation.

1.3.1. The main components of the intelligent system.

Sensors and Interfaces for data collection.

Intelligent systems often use sensors to collect data from the environment or objects. For example, in the aviation industry, these can be sensors that measure vibration, temperature, pressure, wear of parts, etc.

Knowledge base.

It is a repository where the information and rules needed to make decisions are stored. In the case of an intelligent predictive system, the knowledge base may include historical maintenance data, part failure data, component specifications, etc.

Machine learning algorithms.

The system uses MH algorithms to analyze the collected data and create models that can predict future events or outcomes. In our case, algorithms can predict the remaining resource of parts based on data about their current condition and operating conditions.

Analytical tools.

Intelligent systems use a variety of analytical tools to identify patterns, trends, and anomalies in data. These tools help identify potential problems before they become critical.

User interface.

Intelligent systems have convenient interfaces for interaction with the user. They provide information in an understandable form, which allows you to make informed decisions. For example, the system can alert technical personnel about the need to replace a part or perform routine maintenance.

Classification of intelligent systems:

1. Expert systems:

Software systems that use a knowledge base and rules to simulate the decision-making process of an expert in a particular field.

2. Neural networks:

Computer models simulating the work of the human brain for pattern recognition and identifying complex patterns in large data sets.

3. Systems based on machine learning:

Use algorithms that learn from data to perform tasks without being explicitly programmed to perform them.

4. Natural language processing (NLP) systems:

Used to interact with people using natural language, such as chatbots or automatic translation systems.

1.3.2 Application of intelligent systems.

Intelligent systems are used in various industries, including:

Aviation: Predicting the condition of parts, optimizing routes, automating maintenance.

Medicine: Diagnosis of diseases, personalized treatment, management of medical data.

Finance: Fraud detection, risk management, forecasting of market trends.

Production: Quality control, management of production processes, forecasting of inventory needs.

Intelligent systems significantly increase efficiency and accuracy in various processes, ensuring speed and reliability of decision-making based on data.

1.4. Transformers

Transformers represent the latest architecture in machine learning and artificial intelligence, which has revolutionized natural language processing and other tasks involving sequences of data. First introduced in the paper "Attention Is All You Need" by researchers from Google in 2017, the transformer quickly gained popularity due to its ability to efficiently process large amounts of data and perform complex tasks. In this study, we will focus on the application of transformers to predict the technical condition of aircraft parts[5].

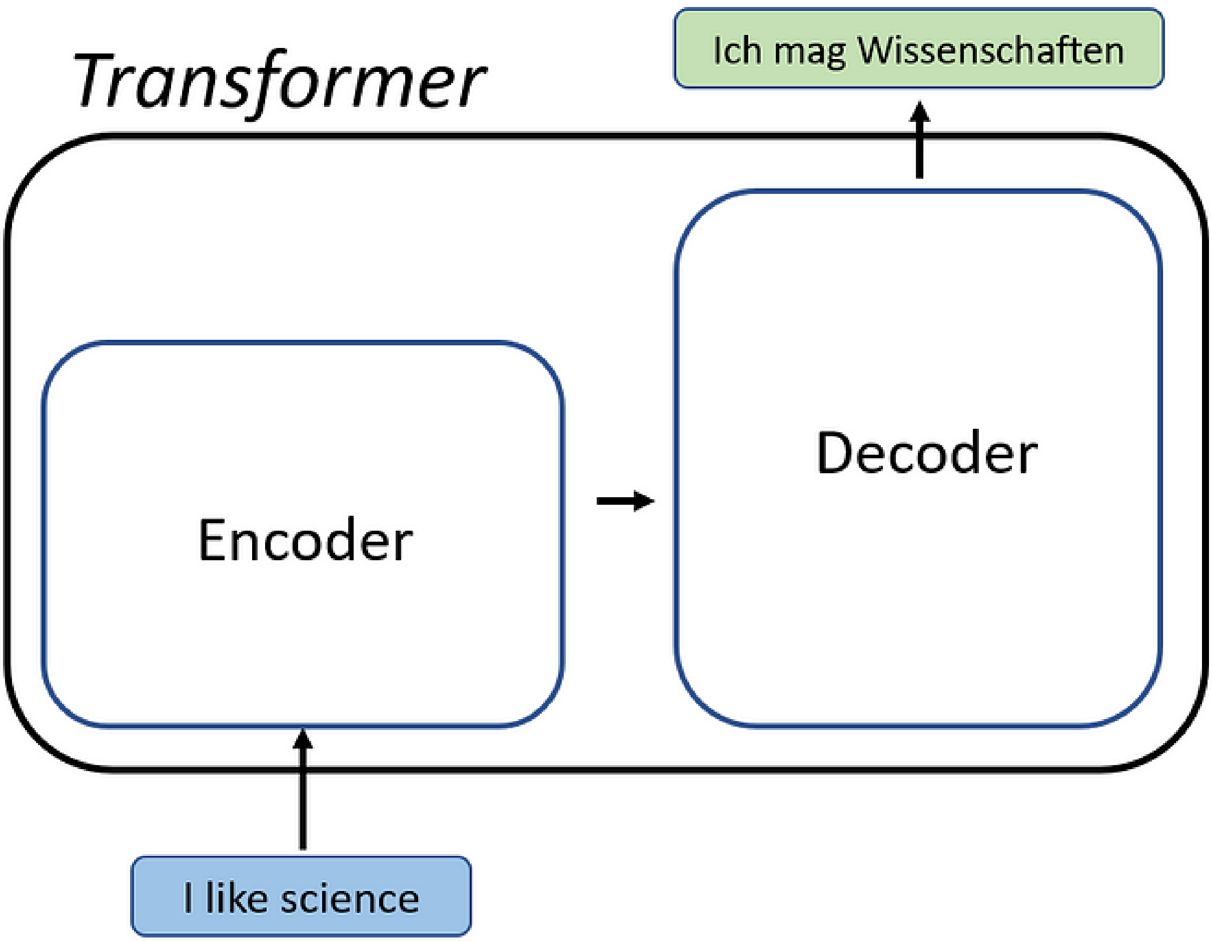

Fig. 1.1. Transformer architecture

Introduction

Transformers perform an "attention" (attention) mechanism that allows the model to focus on important parts of the input data when processing each element of complexity. The main components of transformers are:

1.4.1. Attention Mechanism

This is the key element of the transformer, which allows you to determine which parts of the input are the largest for the current context. The most advanced option is the mechanism of self-attention (self-attention), which allows each element of the complex to pay attention to all other elements[6].

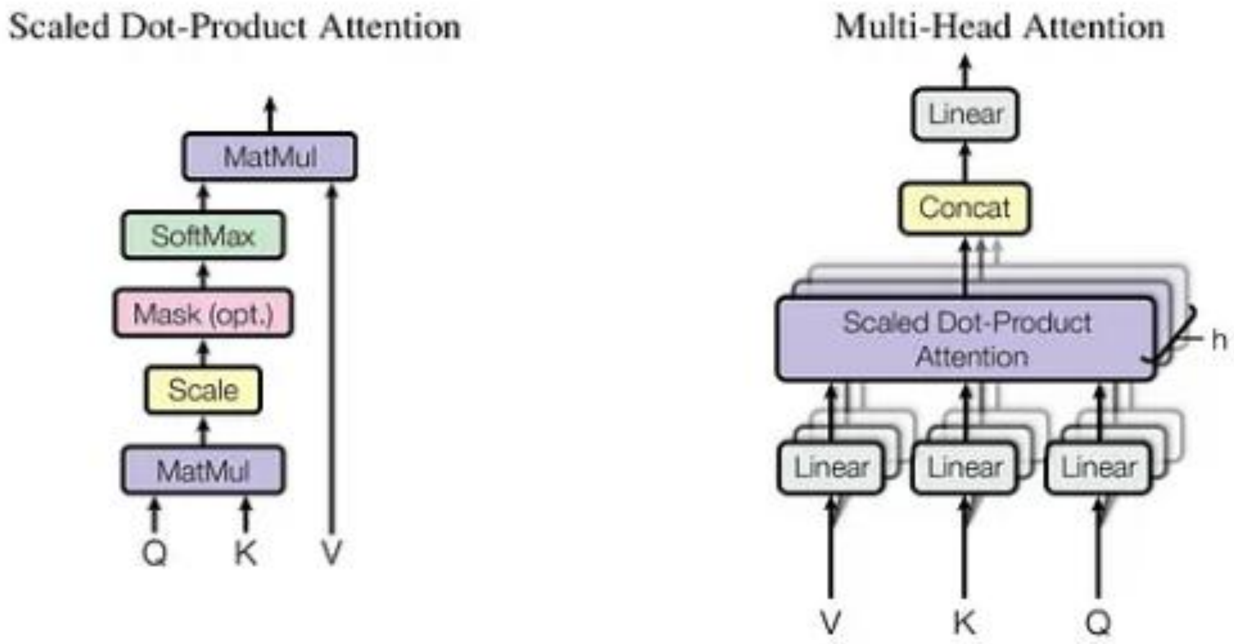

Fig. 1.2. Multi-Head Attention bricks in the model

Consider these multi-headed attention bricks in the model:

Let's start with the left description of the attention-mechanism. It's not very complicated and can be described by the following equation:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

were Q is could be a framework that contains the query (vector representation of one word within the grouping), K are all the keys (vector representations of all the words within the arrangement) and V are the values, which are once more the vector representations of all the words within the arrangement. For the encoder and decoder, multi-head attention modules, V comprises of the same word arrangement than Q. In any case, for the consideration module that's taking under consideration the encoder and the decoder arrangements, V is diverse from the grouping spoken to by Q.

To rearrange this a small bit, we seem say that the values in *V* are increased and summed with a few attention-weights a, where our weights are characterized by:

$$a = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

were weights *a* are defined by how each word of the sequence (represented by *Q*) is influenced by all the other words in the sequence (represented by *K*). Additionally, the SoftMax function is applied to the weights *a* to have a distribution between 0 and 1. Those weights are then applied to all the words in the sequence that are introduced in *V* (same vectors than *Q* for encoder and decoder but different for the module that has encoder and decoder inputs).

The righthand picture portrays how this attention-mechanism can be parallelized into differing defiant that can be utilized side by side. The thought component is rehashed different times with arrange projections of *Q*, *K* and *V*. This gifts the framework to memorize from grouped representations of *Q*, *K* and *V*, which is advantageous to the outline. These straight representations are done by developing *Q*, *K* and *V* by weight systems W that are learned inside the center of the organizing. Those frameworks *Q*, *K* and *V* are specific for each position of the thought modules interior the structure depending on whether they are interior the encoder, decoder or in-between encoder and decoder. The reason is that we got to be go to on either the complete encoder input gathering or a divide of the decoder input course of activity. The multi-head thought module that meddle the encoder and decoder will make past any address that the encoder input-sequence is taken into thought along side the decoder input-sequence up to a given position. After the multi-attention heads in both the encoder and decoder, we have a pointwise feed-forward layer. This small feed-forward organize has hazy parameters for each position, which can be portrayed as a detached, hazy straight modify of each component from the given arrangement.

Preparing

How to prepare such a 'beast'? Preparing and inducing on Seq2Seq models may be a bit diverse from the normal classification issue. The same is genuine for Transformers.

We know that to prepare a show for translation assignments we require two sentences totally different dialects that are interpretations of each other. Once we have a part of sentence sets, we will begin preparing our demonstrate. Let's say we need to decipher French to German. Our encoded input will be a French sentence and the input for the decoder will be a German sentence. However, the decoder input will be moved to the proper by one position. ..Wait, why?

One reason is that we don't need our demonstrate to memorize how to duplicate our decoder input amid preparing, but we need to memorize that given the encoder grouping and a specific decoder grouping, which has been as of now seen by the demonstrate, we anticipate the following word/character.

In the event that we do not move the decoder grouping, the show learns to basically 'copy' the decoder input, since the target word/character for position i would be the word/character i within the decoder input. Hence, by moving the decoder input by one position, our show ought to predict the target word/character for position i having as it were seen the word/characters 1, …, i-1 within the decoder grouping. This avoids our model from learning the copy/paste task. We fill the primary position of the decoder input with a start-of-sentence token, since that put would something else be purge since of the right-shift. Additionally, we add an end-of-sentence token to the decoder input grouping to check the conclusion of that grouping and it is additionally added to the target output sentence. In a minute, we'll see how that's useful for gathering the comes about.

This is genuine for Seq2Seq models and for the Transformer. In addition to the right-shifting, the Transformer applies a cover to the input within the to begin with multi-head attention module to maintain a strategic distance from seeing potential 'future' grouping components. Typically particular to the Transformer architecture since we don't have RNNs where able to input our arrangement consecutively. Here, we input everything together and in the event that there were no cover, the multi-head consideration would consider the complete decoder input grouping at each position.

After the multi-attention heads in both the encoder and decoder, we have a pointwise feed-forward layer. This small feed-forward arrange has indistinguishable parameters for each position, which can be portrayed as a isolated, indistinguishable straight change of each component from the given arrangement.

The self-attention component may be a essential advancement inside the Transformer demonstrate (likely in human advancement as well?), empowering it to observe complicated connections inside information. It permits the demonstrate to weigh the importance of diverse parts of the input independently of their position within the arrangement. This is often especially valuable in scenarios where the setting is basic for understanding the meaning, such as perceiving whether 'it' alludes to the 'wolf' or 'rabbit' in a given sentence.

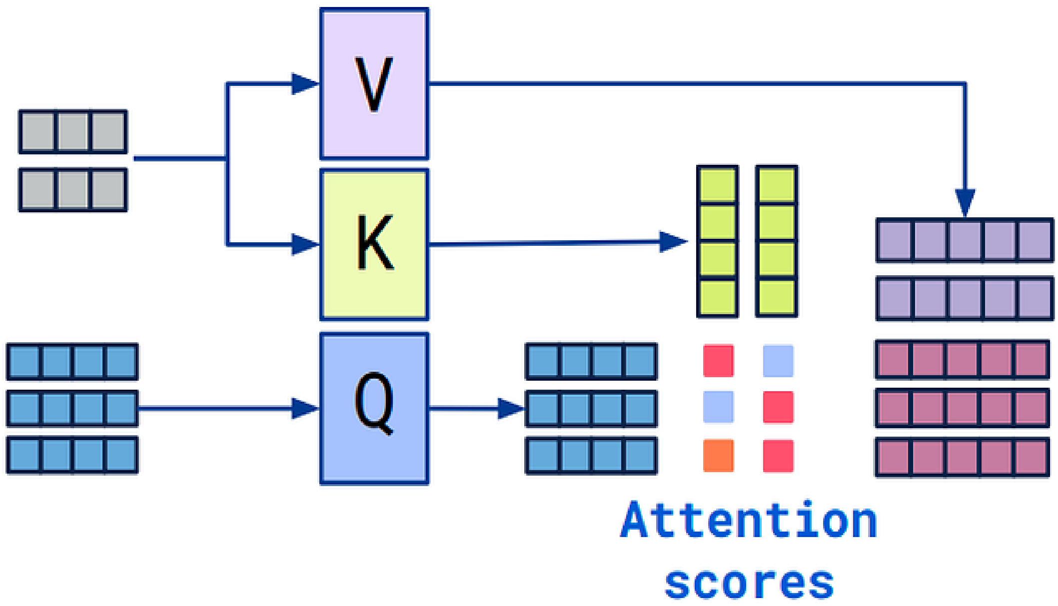

Fig. 1.3. Self-attention mechanism structure

To attain this, the instrument computes three vectors for each input component:a inquiry, a key, and a esteem. The method includes a dab item between each query and key, taken after by a normalization step utilizing SoftMax, and at last, the coming about weights are connected to the esteem vectors, creating the consideration vector. This vector could be a representation that captures the relevant connections inside the input[7].

The style of self-attention lies in its capacity to demonstrate connections without respect to the remove between components within the arrangement. This characteristic may be a stark takeoff from prior grouping modeling approaches, which regularly battled with long-range conditions.

Encoder (Encoder):

The encoder consists of several layers, each of which contains the attention mechanism and feed-forward layers. The coder processes the input data and creates hidden views (hidden views) that contain information about all elements of the page.

Decoder (Decoder):

The decoder also consists of several layers, but it uses both the mechanism of attention itself and the mechanism of attention to the output data (attention encoder-decoder), which allows the model to generate new positions given the input data.

Encoder-Decoder

At the heart of the encoder-decoder show is an ensemble of sequential interpretation of information, where the encoder shapes the input pattern and transforms it into a fixed-length representation, regularly referred to as a tuning vector. This vector serves as a compressed input structure, capturing its quintessence for decoder translation.

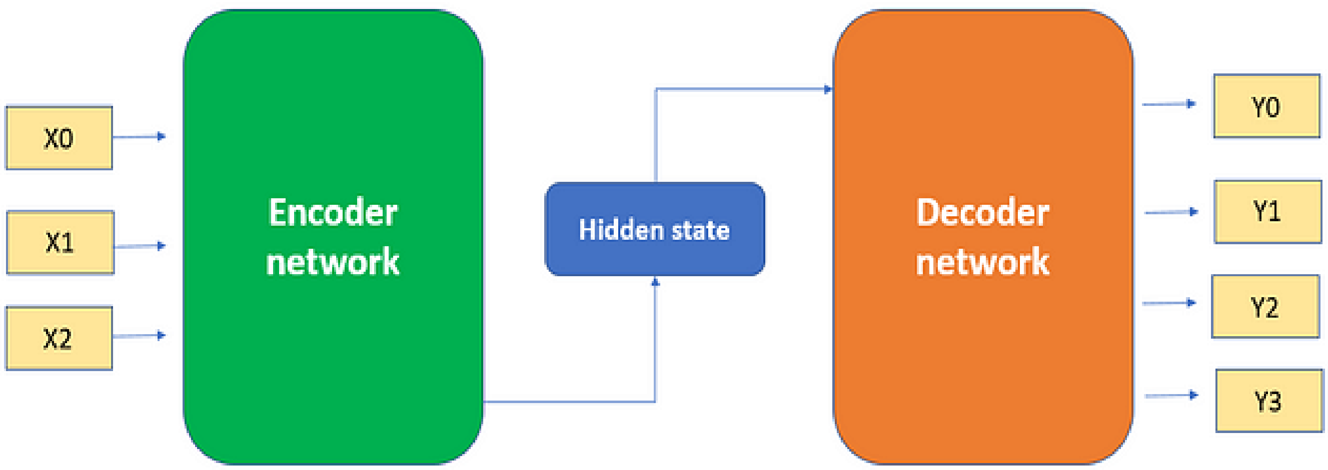

Fig. 1.4. Encoder-Decoder model

1.4.2. Transformer Design

The Transformer engineering, a groundbreaking advancement within the field of profound learning, has revolutionized our approach to sequence-to-sequence errands[8]. At its center, the Transformer comprises of two essential components: an encoder and a decoder.

Each component is planned to perform distinct yet complementary capacities within the preparation of input and era of yield.

The inventiveness of the Multi-Head Consideration instrument lies in its capacity to concurrently prepare information through numerous self-attention layers, each with a one of a kind point of view. This parallel handling empowers the demonstrate to capture a wealthier representation of the input. By isolating the consideration handle into 'heads', the instrument can go to to diverse parts of the input grouping in an unexpected way, associated to how a gather of specialists might analyze different perspectives of a complex issue.

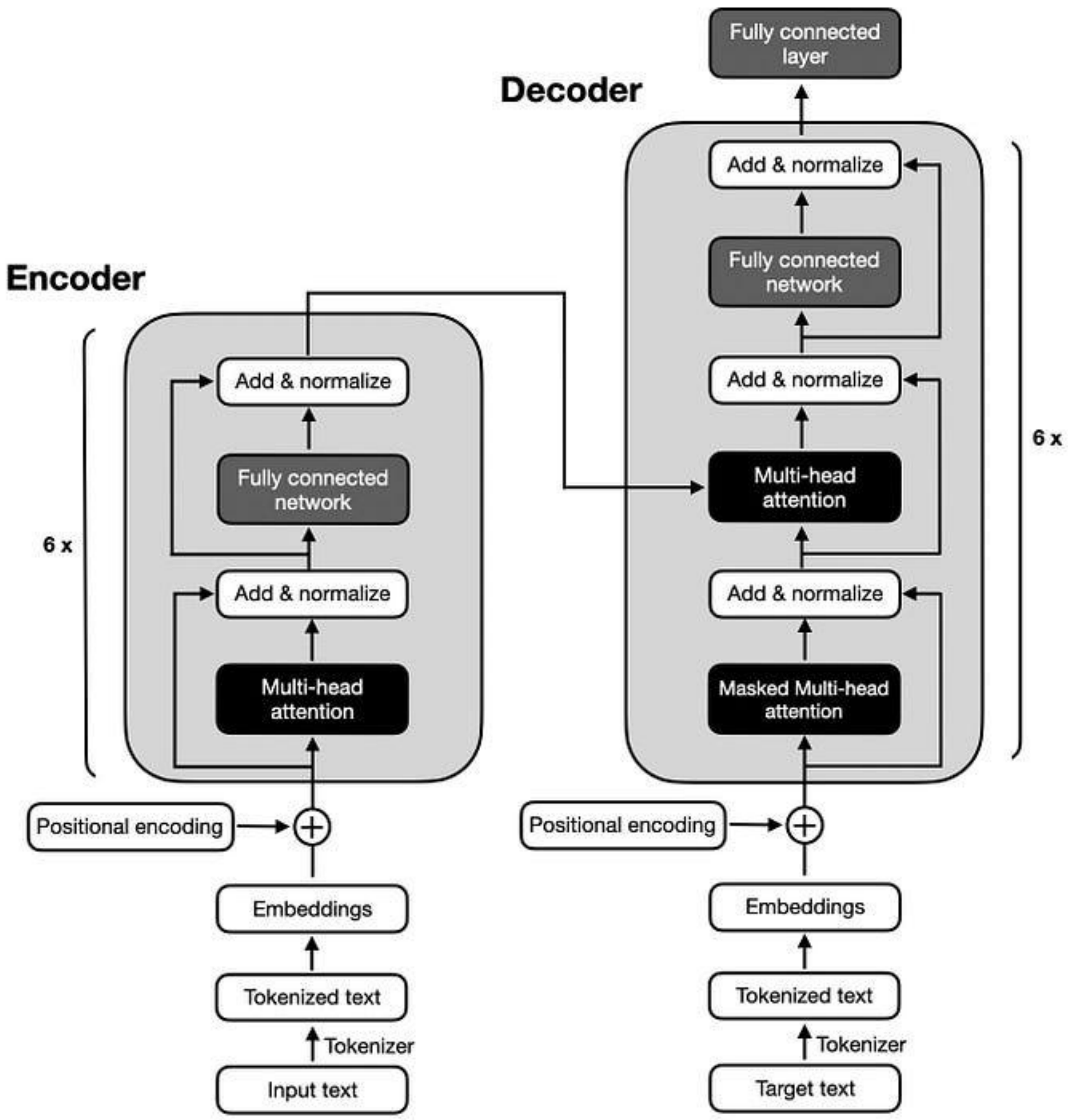

Fig. 1.5. Transformer architecture

Consider the relationship of a group of analysts, each specializing in a distinctive sort of clue. One might center on fingerprints, another on witness explanations, and a third on the timeline of occasions. Together, they develop a comprehensive see of the case. Essentially, Multi-Head Consideration combines the experiences from different consideration 'experts' to create a total understanding of the input information.

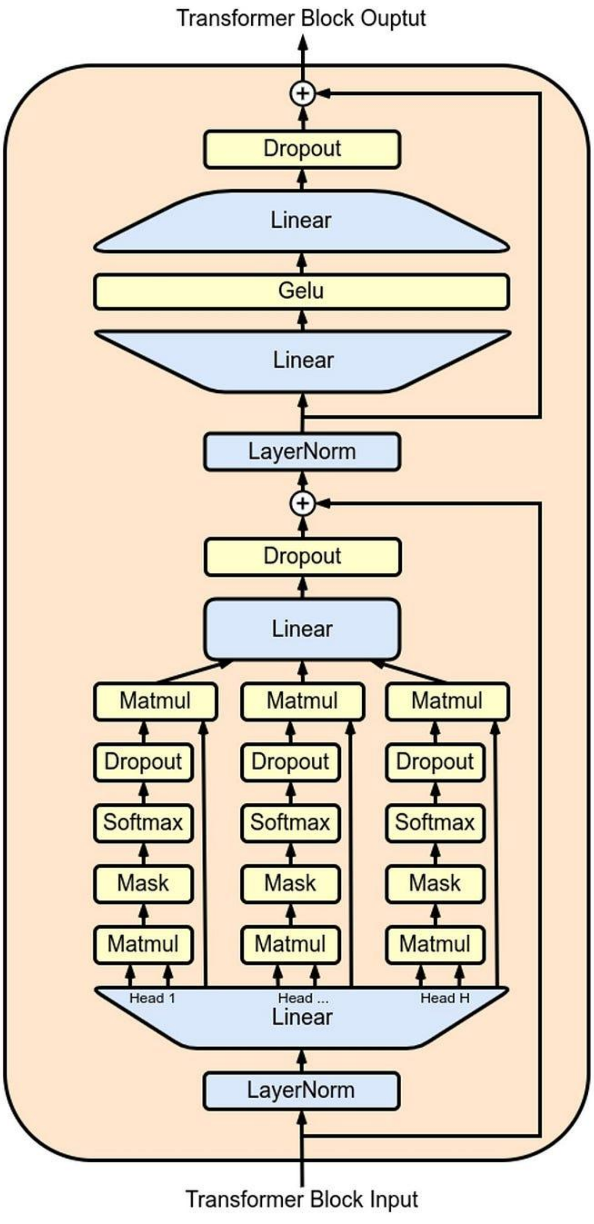

Fig. 1.6. Multi-head transformer structure

The substance of Multi-Head Consideration is to improve the expressiveness of consideration layers without expanding the parameter check essentially. It accomplishes this by running several attention computations in parallel and after that combining their comes about.

The Transformer regularly utilizes 8 such 'heads', in spite of the fact that this number isn't set in stone and can change depending on the model's complexity and the errand at hand. Each head captures distinctive highlights from the input grouping, and their collective yield is concatenated and once once more straightly changed to deliver the ultimate consideration yield. This multi-faceted approach permits the demonstrate to be more perceiving and nuanced in its understanding[9].

1.4.3. Types of transformers and their application

Transformers are artificial intelligence architectures that can process large amounts of data and be used in a variety of machine learning tasks. Since the appearance of the first transformer, many variants and perfections have been developed. Some of the most famous and common transformers are described below.

1. BERT (Bidirectional Encoder Representation from Transformers)

BERT is a bidirectional transformer developed by Google for natural language processing (NLP). Its key feature is the ability to derive context from both words in a sentence[10].

Application: searching for information, classifying texts, identifying the tonality of the text, filling gaps in the text.

Examples of use: Search engines, chat bots, automatic translation.

2. GPT (generative pre-trained transformer)

GPT was developed by OpenAI and is a one-way transformer that generates text based on a given context. It uses an autoencoder to train a large amount of text data.

Application: Generating texts, conducting dialogues, creating content.

Examples of use: Automated systems for writing articles, answering questions, creating a story.

3. RoBERTa (Robustly Optimized Approach to BERT Training)

RoBERTa is an improvement on the BERT model developed by Facebook AI. It optimizes the pre-training process by using larger amounts of data and longer training.

Application: The same problems as BERT, but with improved performance.

Examples of use: Search engines, text analysis, user recognition of users.

4. T5 (Text-to-Text Transformer)

T5 is developed by Google and converts all NLP tasks into text-to-text format. This allows one architecture to be used for a variety of tasks.

Application: Translation, text classification, answering questions, summarizing the text.

Examples of use: Multifunctional language models for various NLP tasks.

5. XLNet

XLNet is a generatively overtrained transformer that compromises the benefits of BERT and autoencoders. It is context-aware in two directions and uses auto-encoding permutation.

Applications: Text analysis, text generation, natural language processing.

Examples of use: Search engines, speech recognition, translation.

6. ALBERT (A Lite BERT)

ALBERT is a more compact version of BERT, designed to reduce computational resources without sacrificing performance.

Application: Same problem as BERT, but with fewer parameters and fast processing[11].

Examples of use: Mobile applications, real-time systems.

7. Vision transformer (ViT)

ViT to transfer the concept of transformers to the field of computer vision. It processes images as a conflict of small patches, similar to processing words in text.

Application: Image classification, segmentation, object recognition.

Examples of use: Automatic pattern recognition systems, medical imaging, self-driving cars.

8. Swin Transformer[12]

Swin Transformer is another variant of the computer image transformer that uses a hierarchical structure to process images at different scales.

Application: Image classification, segmentation, object recognition.

Examples of use: Visual analytics, security systems, robotics.

Advantages of transformers in forecasting tasks

High accuracy: Transformers demonstrate high accuracy in prediction due to the ability to obtain context and relationships between data elements.

Flexibility: They can be adapted to different types of tasks and data, making them versatile machine learning tools.

Scalability: Transformers are easily scalable and can handle large amounts of data with your architecture.

Conclusion

Transformers are powerful tools for solving a wide range of tasks in various industries, including forecasting the technical condition of aircraft parts. They provide high accuracy, flexibility and efficiency, which makes them indispensable in modern artificial intelligence systems. Further development of these transformers and their adaptation to new tasks promises even more opportunities and achievements in the industry.

1.5. Feed-Forward Neural Systems

Inside the Transformer's design, settled between the layers of self-attention, lie the Feed-Forward Neural Systems (FFNNs). These systems are essential in handling the data gathered from the consideration components. Each FFNN comprises of two straight changes with a ReLU enactment in between, a plan choice that permits for the presentation of non-linearity into the something else direct consideration calculations[13].

The part of FFNNs is to freely prepare each position's yield from the consideration layer, guaranteeing that whereas the self-attention component captures the inter-token connections, the FFNNs refine the token representations without modifying their positions. This parallel handling capability may be a stark differentiate to the consecutive nature of RNNs, which prepare inputs in a step-by-step design.

The excellence of FFNNs inside Transformers is their effortlessness and power. They are basic, comprising of fair many straight layers, however they are competent of modeling complex connections after the consideration layers have done their portion in highlighting the pertinent data[14].

In rundown, FFNNs are the unsung heroes of the Transformer demonstrate, giving profundity and complexity to the learning handle. They are the workhorses that apply the same change to diverse positions, permitting for the specialization of the demonstrate in different errands, from dialect understanding to picture acknowledgment.

Comparison of Transformers with RNNs

Feed-Forward Neural Systems

Inside the Transformer's design, settled between the layers of self-attention, lie the Feed-Forward Neural Systems (FFNNs). These systems are essential in handling the data gathered from the consideration components. Each FFNN comprises of two straight changes with a ReLU enactment in between, a plan choice that permits for the presentation of non-linearity into the something else direct consideration calculations.

The coming of Transformers checked a worldview move within the way we approach grouping modeling. Transformers shun the consecutive reliance of RNNs, handling whole groupings in parallel. This architectural advancement leverages the complete might of cutting edge computing equipment, such as GPUs and TPUs, to quicken preparing and deduction times drastically.

1.5.1. Convolutional neural organization and its composition

A convolutional neural arrange (CNN) could be a specialized sort of profound neural organize that's especially successful for handling spatially organized information such as pictures. CNNs consequently extract highlights from input information through the utilization of convolutional layers, making them greatly capable in design acknowledgment, picture classification, natural dialect handling, and numerous other assignments.

Feedforward Neural Systems (FNN) are a fundamental sort of counterfeit neural systems where data moves in as it were one course[15]:

from input to yield through covered up layers. These systems have no criticism, that's, the yield flag of one layer does not influence the input flag of the same or past layers.

Primary components

Input Layer:

Contains neurons that get input. Each neuron within the input layer is dependable for one input parameter.

Covered up layers:

One or more layers between the input and yield layers. Neurons in these layers perform calculations and apply non-linear actuation capacities to make complex designs.

Yield Layer:

Contains neurons that create yield values based on covered up layer preparing.

Guideline of operation

Weighting of input information:

Each input flag is increased by a certain weighting figure. Weights decide the significance of the comparing input for each neuron.

Enactment:

The weighted signals are summed and passed through an enactment work that decides the yield esteem of the neuron. Common actuation capacities are the sigmoid work, hyperbolic digression, ReLU (Amended Straight Unit), and others.

Information exchange:

The yield values of the neurons of one layer are transmitted as input values to the neurons of the following layer.

Preparing of coordinate neural systems

Preparing of coordinate neural systems more often than not happens utilizing the strategy of backpropagation. This handle incorporates:

Forward Engendering:

The input is passed through the organize and the yield is calculated.

Blunder calculation:

The contrast between the real yield and the specified yield characterizes the mistake for each yield neuron.

Backpropagation:

The blunder is nourished back through the organize and the weights are balanced to play down the mistake. The weights are balanced employing a gradient plunge calculation that changes the weights in extent to their commitment to the overall blunder.

Preferences and drawbacks

Focal points:

Effortlessness:

Feedforward neural systems are among the only sorts of neural systems, making them simple to execute and get it.

Adequacy:

They are successful in tackling a wide extend of assignments, counting classification, relapse, design acknowledgment.

Drawbacks:

Difficulty of handling time information:

Coordinate neural systems cannot take under consideration the time arrangement and relationship of information.

Tuning complexity:

Deciding the ideal number of covered up layers and neurons, as well as tuning other parameters, can be challenging.

Issues with huge information:

Increasing the number of layers and neurons can lead to a critical increment in computational complexity and preparing time.

Application

Coordinate neural systems are utilized in many areas, such as:

Picture acknowledgment:

Image classification, penmanship acknowledgment.

Flag handling:

Sound flag investigation, time arrangement estimating.

Monetary estimates:

Forecasting stock costs, chance investigation.

Medication:

Diagnosis of maladies based on therapeutic pictures or biometric information.

Robotization:

Control frameworks, robotics.

Conclusion

Coordinate neural systems are an important and effective instrument within the field of machine learning and manufactured insights. They are well suited for a wide run of errands where classification or relapse based on inactive information is required. At the same time, for assignments that require the handling of arrangements or time information, it is way better to utilize other sorts of neural systems, such as repetitive neural systems or transformers.

1.5.2. Comparison of Transformers with RNNs

Consecutive vs. Parallel Preparing[16]

The appearance of Transformers stamped a worldview move within the way we approach arrangement modeling. Transformers shun the consecutive reliance of RNNs, preparing whole arrangements in parallel. This architectural development leverages the total might of cutting edge computing equipment, such as GPUs and TPUs, to quicken preparing and deduction times dramatically.

The parallel preparing ability of Transformers isn't without its trade-offs. A striking one is the expanded number of parameters, which requests more memory and computational assets.

Whereas RNNs prepare information step-by-step, carrying forward a covered up state that typifies past data, Transformers work on the complete grouping at once. This permits for the simultaneous processing of information, which may be a boon for effectiveness but presents challenges in interpretability. The Table 1.2 underneath concisely contrasts the preparing characteristics of RNNs and Transformers.

Table 1.2

Aspect	**RNNs**	**Transformers**
Processing method	Sequential	Parallel
Training speed	Slower	Faster
Hardware Utilization	Limited	Optimized
Parameter count	Lower	Highter

In quintessence, whereas RNNs have a characteristic advantage in assignments with solid transient conditions, Transformers exceed expectations in scenarios where the capacity to handle expansive groupings in parallel and capture long-range conditions is vital.

Long-Range Conditions

One of the foremost striking highlights of Transformers is their intrinsic capacity to handle long-range conditions with aplomb. This characteristic is significant for understanding the setting in arrangements where pertinent data may be isolated by significant separations. Conventional Repetitive Neural Systems (RNNs), counting their more progressed variations like Long Short-Term Memory (LSTM) systems, regularly hook with the vanishing angle issue. This issue causes the impact of starting inputs to melt away as the grouping advances, making it arduous for these models to preserve setting over long groupings.

Transformers, by differentiate, are not obliged by arrangement length[17]. Their self-attention instrument computes the significance of all parts of the input arrangement at the same time, allowing for a worldwide understanding of the information. Usually a game-changer for assignments that require the blend of data spread over a complete arrangement, such as report summarization or address replying.

The taking after list depicts the comparative points of interest of Transformers over RNNs in taking care of long-range conditions:

Transformers:

Utilize self-attention to weigh the significance of each component within the grouping, in any case of remove.

RNNs:

Consecutive preparing can lead to reduced impact from prior components, particularly in longer sequences.

LSTMs:

Join gating instruments to superior hold data over time, but still confront challenges with exceptionally long groupings.

In substance, the Transformer design has re-imagined the scene of arrangement modeling by giving a strong arrangement to the long-standing challenge of long-range conditions. This has opened up unused vistas within the field of machine learning, especially in complex assignments that require profound relevant understanding.

1.5.3. Applications of Transformers

NLP and Language Modeling

In the domain of Characteristic Dialect Preparing (NLP), transformers have introduced in a unused "epoch" of dialect modeling ability. Transformers, with their consideration components, have ended up the foundation of cutting edge NLP, exceeding expectations in capturing setting and relationships between words. This has driven to critical progressions in different applications, from sentiment analysis to dialect interpretation, and the advancement of advanced chatbots and virtual collaborators[18].

The self-attention instrument inside transformers permits for the nuanced understanding of dialect, empowering models to prepare words in connection to all other words in a sentence, instead of in confinement.

Underneath grandstands a few of the spearheading models in NLP that have utilized transformer engineering(seen Table 1.2):

Table 1.3

Model	Release Year	Highlight Feature
BERT	2018	Bidirectional context understanding
XLNet	2019	Generalized autoregressive pretraining
GPT–3	2020	Generative pre-trained capabilities

In spite of their momentous capabilities, transformers in NLP are not without challenges. Equivocalness and setting understanding stay critical obstacles, as dialect is inalienably nuanced and regularly context-dependent.

The nonstop advancement of transformer models points to address these complexities, pushing the boundaries of what machines can comprehend and how they associated with human dialect.

Computer Vision

The appearance of Transformers in computer vision marks a worldview move from the routine convolutional neural systems (CNNs) that overwhelmed the field for a long time. Transformers present a novel approach to handling visual information, leveraging self-attention components to capture worldwide conditions inside an picture. This permits for a more nuanced understanding of the visual setting, which is especially useful for errands such as protest discovery, picture division, and classification.

The progressive structure of vision transformers, such as the Swin Transformer, empowers the demonstrate to center on diverse scales of an picture, improving the capacity to perceive fine subtle elements whereas keeping up a worldwide viewpoint.

Later headways have seen Transformers being connected to a assortment of restorative imaging errands, illustrating their flexibility and potential for making strides symptomatic precision. For occasion, vision transformers have been utilized for COVID-19 screening from radiography, lung cancer guess, and retina vessel division.

The integration of Transformers into computer vision isn't fair a specialized advancement; it is reshaping the scene of conceivable outcomes inside the field. As we proceed to investigate and refine these models, able to anticipate to see indeed more groundbreaking applications that thrust the boundaries of what machines can see and get it.

Conclusion

In conclusion, the presentation to Transformers and Consideration Components has shed light on the progressive progressions in modeling consecutive information.

Transformers, with their self-attention component, have outperformed conventional models like RNNs and LSTMs in different assignments, especially in dialect modeling and content generation.

The significance of consideration in Transformers cannot be exaggerated, because it empowers the demonstrate to weigh the importance of diverse input tokens and capture long-range conditions without successive preparing. As we dive more profound into the domain of NLP and Computer Vision, Transformers proceed to play a essential part, exhibiting their ability in dealing with complex information structures with artfulness and effectiveness.

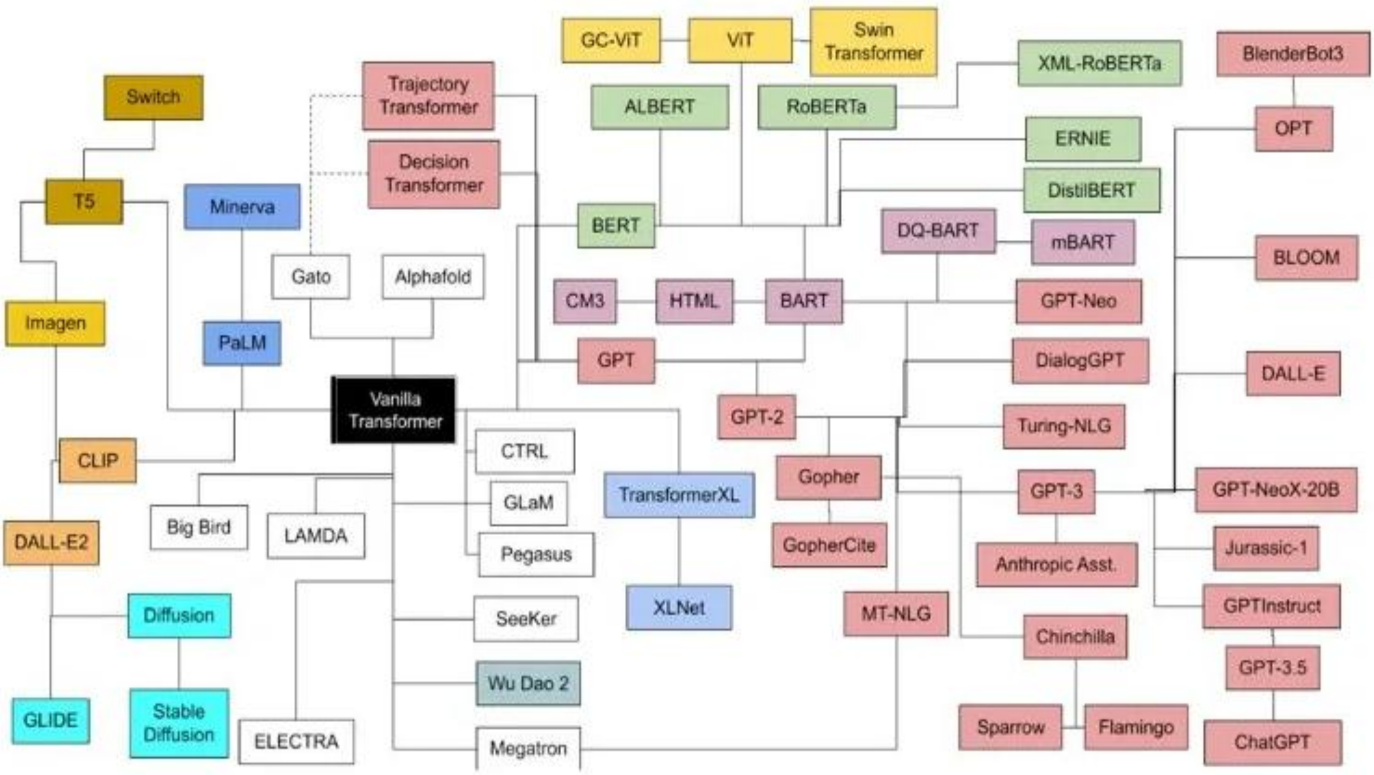

Fig. 1.7. Transformers family tree

1.6. Application of transformers to time arrangement models

Utilize counterfeit insights to make strides information estimating comes about.

Within the sprawling scene of machine learning, transformers stand tall as building wonders, reshaping the way we prepare and comprehend endless sums of information with their complicated plans and capacity to capture complex connections.

Since the creation of the primary transformer in 2017, there's been an blast of transformer sorts, counting capable generative AI models such as ChatGPT and DALL-E.

Whereas transformers are compelling in text-to-text or text-to-image models, there are a few challenges when applying transformers to time arrangement[19]. At the Open Source Summit North America 2023, Ezequiel Lanza shared the issues with current transformer models and presented modern transformers that are starting to appear promising comes about for time arrangement.

1.6.1. Diagram of Transformer Usefulness

Let's see at a transformer's part in Steady Dissemination, a profound learning show that can turn a express, such as “A puppy wearing glasses,” into an picture. The transformer gets the content inputted by the client and produces content embeddings. Content embeddings are a representation of the content that can be studied by a convolutional neural arrange (CNN) — in this case, a U-NET. Whereas Steady Dissemination models utilize embeddings to create pictures, embeddings can be utilized to create extra yields that are valuable for time arrangement models.

How Transformers Work

To get it how to apply a transformer to a time arrangement demonstrate, we have to be center on three key parts of the transformer engineering:

Implanting and positional encoding

Encoder:

Calculating multi-head self-attention

Decoder:

Calculating multi-head self-attention

As an case, we'll clarify how vanilla transformers work, a transformer that deciphers straightforward expressions from one dialect into another.

Implanting and positional encoding:

How you speak to your input information

After you input the state “I adore dogs” into a vanilla transformer, an calculation called Word2Vec changes over each word into a list of numbers, called a vector. Each vector contains data approximately what the word implies and how it's related to other words, such as equivalent words and antonyms.

A demonstrate must too get it the position of each word in a state. For occasion, “dogs I love” does not have the same meaning as “I cherish dogs.” A moment calculation called positional vector employments a complex numerical condition to assist your demonstrate get it sentence order. Packaged together, data given by Word2Vec and positional vector calculations is what's known as a content inserting, or your unique express spoken to in a way a machine can examine.

Multi-head Self-attention at the Encoder Level.

Another, encoders get the text embeddings and change over them into unused vectors, including data to assist the demonstrate perceive the relationship between words in a express. For example, within the state “Children playing within the park,” an encoder would dole out the foremost weight to “children,” “playing,” and “park.” We call this handle self-attention since it directs which words the show ought to pay most consideration to.

To calculate self-attention, encoders make three vectors — a inquiry vector, a key vector, and a esteem vector — for each word. The vectors are made by increasing the express against three frameworks. It's a complex calculation, but the critical portion to get it is that each word in a state gets duplicated by each other word in a express, and it can take a parcel of time to calculate the consideration of long expressions.

To create an indeed superior understanding of the relationship between words, the self-attention layer can run numerous heads at once. This prepare is called multi-head consideration, and it permits the show to center on distinctive parts of a state at the same time, such as when there are short- and long-term conditions. For illustration, within the express “The animal didn't cross the street since it was as well tired,” multi-head consideration tells the show that “animal” and “it” allude to the same idea.

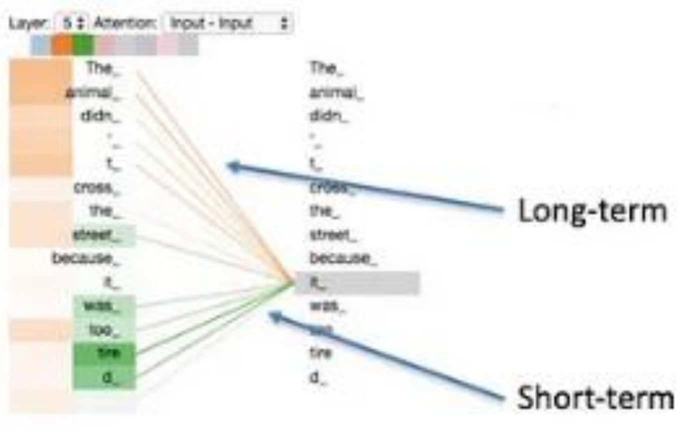

Fig. 1.8. Structure of the self-attention mechanism of the two-headed transformer

The decoder works the same way as the encoder, but it has been prepared employing a different data set. For case, in a vanilla transformer, in the event that the encoder has been prepared on English dialect information and the decoder on French information, the decoder will run the same multi-head self-attention calculations to interpret the first express into French[20].

1.6.2. Utilizing Transformers for Time Arrangement

Why doesn't this transformer engineering work for time arrangement? Time arrangement acts like a dialect in a few ways, but it's distinctive than conventional dialects. In dialect, you'll express the same thought utilizing unfathomably distinctive words or sentence orders. Once a language-based transformer such as vanilla has been prepared on a dialect, it can understand the relationship between words, so once you speak to an thought in two distinctive inputs, the transformer will still arrive at generally the same meaning. Time arrangement, in any case, requires a strict arrangement — the arrange of the information focuses matter much more. This presents a challenge for utilizing transformers for time arrangement[21].

Current Approaches:

The autoregressive coordinates moving normal (ARIMA) show works for a few time arrangement but requires a profound understanding of related patterns, regular changes, and remaining values — and indeed at that point it as it were works for straight conditions. In numerous time arrangement that include multivariate issues, the relationship between conditions isn't straight and ARIMA will not work.

There are too a few approaches that utilize neural systems:

Feedforward neural organize (FNN) models utilize any past six information focuses in a arrangement to foresee the another six. In spite of the fact that FNNs empower nonlinear conditions, they require you to handcraft a show that centers on exceptionally particular issues or subsets of information, making this show as well time expending to develop for expansive information sets.

In a repetitive neural network (RNN) demonstrate, you'll bolster the show a little subset of information focuses that are significant to your time arrangement, and cells within the RNN will memorize which information focuses are vital and what their weight is. In any case, when you're managing with information sets that have long conditions, the weight gets to be less important, and the model's precision lessens over time.

Long short-term memory (LSTM) models are comparative to RNNs, but that each cell encompasses a memory that permits you to overhaul the weight more habitually amid long arrangements. This makes LSTM a good solution for a few utilize cases.

Seq2seq could be a way to make strides LSTM execution. Rather than nourishing your arrange straightforwardly, you'll be able bolster your information into an encoder, which produces highlights of your input that get bolstered into the decoder.

Improving time series using transformers:

Utilizing multi-head consideration empowered by transformers seem offer assistance progress the way time arrangement models handle long-term conditions, advertising benefits over current approaches. To grant you an thought of how well transformers work for long conditions, think of the long and nitty gritty reactions that ChatGPT can produce in language-based models. Applying multi-head consideration to time arrangement may create comparable benefits by permitting one head to center on long-term conditions whereas another head centers on short-term conditions. We accept transformers might make it conceivable for time arrangement models to anticipate as numerous as 1,000 information focuses into long haul, on the off chance that not more.

The Quadratic Complexity Issue:

The way transformers calculate multi-head self-attention is tricky for time arrangement. Since information focuses in a arrangement must be increased by each other information point within the arrangement, each information point you include to your input exponentially increments the time it takes to calculate consideration. This is often called quadratic complexity, and it makes a computational bottleneck when managing with long arrangements.

CHAPTER 2
FUNDAMENTALS OF MACHINE LEARNING

2.1. Machine learning

Machine learning (ML) is a group of methods in the field of artificial intelligence, a set of algorithms that are used to create a machine that learns from its own experience. As training, the machine processes huge arrays of input data and finds patterns in them.

2.1.1. Methods of machine learning

Within the most common case, two sorts of machine learning are recognized:

Learning by points of reference, or inductive learning, and deductive learning. Since the last mentioned is as a rule credited to the space of master frameworks, the terms "machine learning" and "learning from points of reference" can be considered synonymous. This strategy of learning is presently, as they say, in drift, but master frameworks are encountering a emergency. The information bases basic them are troublesome to accommodate with the social information show, so mechanical DBMSs cannot be viably utilized to fill the information bases of master frameworks[22].

Learning by points of reference, in turn, is isolated into three fundamental sorts: directed learning, or learning with a instructor (directed learning), unsupervised learning, or learning without a educator, and learning with support (fortification learning).

In expansion to the over, other strategies of learning are being created: dynamic, multitasking, assorted, exchange, etc. "Profound learning" has been creating particularly effectively in later a long time, utilizing which learning calculations with a educator and without a instructor can be effectively combined.

2.1.2. Controlled learning

In this type of training, the model is trained on labeled data, where each input example has a corresponding output.

The main tasks: classification (determining the category of the object) and regression (prediction of the numerical value).

This learning strategy is utilized in cases where there are expansive sums of information, let's say - thousands of photographs of pets with markers (names, names): typically a cat, typically a pooch. It is vital to make an calculation by which the machine may, based on a photo it had not "seen" some time recently, decide who is delineated on it: a cat or a canine. The part of "educator" in this case is played by a individual who has placed markers in progress. The machine itself chooses the signs by which it recognizes cats from mutts. Subsequently, within the future, the calculation she found can be rapidly reconfigured to unravel another issue, for case, to recognize chickens and ducks. The machine will once once more perform the troublesome and careful work of distinguishing the signs by which these fowls will be recognized. And the neural organize, which was instructed to recognize cats, can be rapidly prepared to handle the comes about of computer tomography[23].

2.1.3. Unsupervised learning

The model is trained on unlabeled data and looks for hidden structures or patterns in the data.

Main tasks: clustering (grouping of objects) and dimensionality reduction (reducing the number of features).

In spite of the fact that checked, labeled information has as of now amassed very a part, information without markers (names) is still much more. These are pictures without captions, sound recordings without comments, writings without explanations. The errand of the machine amid unsupervised learning is to discover the association between partitioned information, recognize designs, choose up designs, organize data or depict their structure, perform information classification. Unsupervised learning is used, for case, in recommender frameworks, when in an internet store, based on the examination of past buys, the buyer is advertised items which will intrigued him with a better likelihood than others. Or when, after observing a video clip on the YouTube entry, the guest is offered handfuls of joins to recordings to some degree comparable to the one seen. Or when Google, in reaction to the same inquiry, positions a link within the look comes about for one client in an unexpected way than for another, since it takes into consideration the look history[24].

2.1.4. Neural networks and deep learning

Such learning could be a extraordinary case of controlled learning, but the instructor in this case is the "environment". The machine (it is regularly called an "operator" in this circumstance) has no earlier data almost the environment, but has the capacity to perform any activities in it[25]. The environment responds to these activities and in this manner gives the operator with information that permits it to respond and learn from them. In reality, the specialist and the environment shape a input framework.

Fortification learning is utilized to fathom more complex errands than tutored and untutored learning. It is utilized, for illustration, in navigation systems for robots that learn to maintain a strategic distance from collisions with obstacles by picking up involvement, getting input at each collision. Support learning is additionally utilized in logistics, when drawing up plans and arranging errands, when educating a machine rationale diversions (poker, backgammon, Go, etc.).

2.1.5. Neural systems and profound learning

Distinctive advances and calculations are utilized for machine learning. In specific, discriminant examination, Bayesian classifiers and many other scientific strategies can be utilized. But at the conclusion of the 20th century, more and more consideration started to be paid to counterfeit neural systems (ANN). Another explosion of intrigued in them started in 1986, after the critical advancement of the so-called "The strategy of backpropagation of the blunder", which was effectively connected within the preparing of a neural organize.

ANN may be a framework of associated and connection manufactured neurons made on the premise of generally straightforward processors. Each ANN processor occasionally gets signals from a few processors (either from sensors or from other flag sources) and occasionally sends signals to other processors. Together, these basic processors, associated to a organize, are able of understanding very complex errands[26].

Most regularly, neurons are found within the network by levels (they are moreover called layers). Neurons of the primary level are, as a run the show, input. They get information from the exterior (for illustration, from the sensors of the confront acknowledgment framework) and, after preparing them, transmit driving forces through the neural connections of neurons at the another level. Neurons at the moment level (it is called covered up, since it isn't straightforwardly associated to either the input or the yield of the ANN) prepare the gotten motivations and transmit them to the neurons at the yield level. Since we are talking almost the recreation of neurons, each processor of the input level is associated to a few processors of the covered up level, each of which, in turn, is associated to a few processors of the yield level[27].

2.2. Choice of learning model

For shrewdly prescient frameworks based on transformers, the foremost appropriate machine learning strategy is Fortification Learning or Administered Learning, depending on the particular assignment[28].

2.2.1. Administered learning

Administered learning is commonly utilized for expectation issues since it has the taking after preferences:

Precision and consistency:

Models are prepared on labeled information, permitting exact forecasts of future occasions based on authentic information.

Assortment of models:

There are numerous calculations for administered learning, counting transformers, that work well with huge information groupings.

Application to time arrangement:

Transformers can be viably utilized for time arrangement examination and determining due to their capacity to prepare arrangements of data.

Transformers are an awfully effective instrument for directed learning, particularly when managing with successive information. Their key highlights, such as the consideration component, permit for effective taking care of of conditions between diverse pieces of information, making them perfect for determining assignments[29].

2.2.2. Fortification Learning

Support learning can be connected in some forecast scenarios, particularly when it is necessary to form steady choices or adjust to changes within the environment[30]. Benefits of fortification learning incorporate:

Flexibility:

The framework can learn from intuitive with the environment and alter its activities to maximize rewards.

Methodology learning:

Utilized to create methodologies that can adjust to energetic conditions and changes within the environment.

Be that as it may, fortification learning can be more troublesome to execute and requires critical computational assets, particularly for expansive frameworks.

Conclusion

For most transformer-based forecast errands, administered learning will be the foremost fitting strategy. Transformers appear tall effectiveness when working with consecutive data and permit you to form precise and dependable determining models.

Thus, for intelligent prediction systems based on transformers, supervised learning is best suited, after which it provides high accuracy and predictability of results.

2.3. Batabase selection

Databases are organized collections of data stored and managed by electronic means. There are several types of databases, each of which is suitable for different types of tasks and has its own advantages and disadvantages[31].

Databases are a essential component of cutting edge data frameworks that permit putting away, organizing and overseeing expansive sums of information. They are utilized in a assortment of businesses, from trade and pharmaceutical to science and innovation.

2.3.1. Sorts of databases

1. Social databases (RDBMS):

- tables are utilized to store information.

- connections between information are communicated utilizing essential and remote keys.

Illustrations: MySQL, PostgreSQL, Prophet, Microsoft SQL Server.

1 NoSQL database:

- planned for working with unstructured or semi-structured information.

- incorporate diverse sorts such as document-oriented, chart, column and key-value databases.

Illustrations: MongoDB, Cassandra, Neo4j, Redis.

2 Object-oriented databases:

- store information within the shape of objects, as in object-oriented programming.
- cases: db4o, ObjectDB.

3 Other sorts of databases

Other specialized databases, such as chart databases, time-series databases, spatial databases, etc.

2.3.2. Fundamental components of databases

Tables are the most component of social databases, where information is put away in columns and columns.

Questions (SQL) could be a organized inquiry dialect utilized to recover and control information in social databases.

Records are structures that progress the speed of information recovery in tables.

Exchanges are a grouping of activities that are executed as a single unit, guaranteeing information judgment.

2.3.3. Preferences of utilizing databases

Information keenness — guarantee consistency and rightness of information.

Security - permit you to arrange get to levels and ensure information from unauthorized get to.

Adaptability - back work with huge sums of information and can be scaled on a level plane or vertically.

Blame resilience - provide reinforcement and recuperation of information within the occasion of a disappointment.

2.3.4. Impediments and challenges

Complexity of Organization - Requires specialized information to set up and keep up.

Fetched — can be costly to actualize and keep up, particularly undertaking arrangements.

Execution - Expansive sums of information or complex questions can require noteworthy assets.

2.3.5. Utilize of databases in different businesses

Trade — administration of customer information, monetary records, stock.

Pharmaceutical — capacity of electronic restorative records, inquire about and clinical information.

Science — examination of enormous information, capacity of investigate comes about.

Innovations — client information administration, handling of huge volumes of information.

Conclusion

Databases are an necessarily portion of cutting edge data frameworks that give compelling information capacity, get to and administration. They proceed to create, reacting to modern challenges and needs emerging in different areas of movement.

2.4. Database requirements

For cleverly frameworks for foreseeing the require for substitution of flying machine parts based on transformers, it is vital to select a database that can productively handle huge volumes of information, bolsters quick get to to data, and permits putting away different sorts of information (organized, semi-structured and unstructured).

Essential database prerequisites[32]:

- Tall execution and adaptability — the database must bolster tall studied and type in speeds, as well as be able of even scaling.

- Adaptability in putting away diverse sorts of information - the framework must effectively store and handle both conventional social information and semi-structured information (such as JSON).

- Expository Inquiry Back - Must be able to run complex expository questions to pick up experiences from information.

Depiction:

PostgreSQL may be a effective open source social database that supports complex questions and exchanges. TimescaleDB may be a PostgreSQL expansion optimized for working with time arrangement, which is exceptionally critical for analyzing information collected in genuine time[33].

Focal points:

Adaptability, back for complex questions, proficient capacity and preparing of time information.

MongoDB

Portrayal:

A document-oriented NoSQL database that stores information within the organize of JSON-like archives. This makes it simple to work with semi-structured information.

Preferences:

Adaptability in information capacity, tall execution, adaptability, ease of working with different information.

Elasticsearch

Portrayal:

A look and analytics framework that permits you to effectively list and look huge volumes of information in genuine time.

Preferences:

Quick look and analytics, bolster for diverse sorts of information, integration with other frameworks (for case, Kibana for visualization).

Apache Cassandra

Depiction:

A disseminated NoSQL database outlined to handle expansive volumes of information dispersed over different servers, giving tall accessibility without a single point of disappointment.

Preferences:

Versatility, tall accessibility, resistance to disappointments, reasonable for working with huge sums of data.

Conclusion

For the framework of determining the require for substitution of airplane parts based on transformers, the foremost reasonable databases are PostgreSQL with the MongoDB. PostgreSQL with MongoDB will give adaptability in putting away and handling distinctive sorts of information.

CHAPTER 3
SYSTEM DATA BASES DEVELOPMENT

3.1. MongoDB connection

To connect to a PostgreSQL database using Python, we will use the psycopg2 library, which is a popular PostgreSQL adapter for Python. At the same time, we can use the pymongo library to connect to MongoDB.

3.1.1. Connecting to PostgreSQL using psycopg2:

```
# We install the psycopg2 library:
pip install psycopg2-binary sqlalchemy transformers torch
pip install torch transformers pandas scikit-learn
# Code for connecting to PostgreSQL:
import psycopg2
from psycopg2 import sql

# Loading data from the table
query = "SELECT * FROM aviation_data"
data = pd.read_sql(query, engine)

# Data to connect to PostgreSQL
db_config = {
 'dbname': 'your_database_name',
 'user': 'your_username',
 'password': 'your_password',
 'host': 'your_host',
 'port': 'your_port'
}

try:
 # Connection to the database
```

```
 connection = psycopg2.connect(**db_config)
 cursor = connection.cursor()

 # Execution of a simple query
 cursor.execute('SELECT version();')
 db_version = cursor.fetchone()
 print(f'PostgreSQL database version: {db_version}')

 # Close the cursor and connect
 cursor.close()
 connection.close()

except (Exception, psycopg2.Error) as error:
 print(f'Error while connecting to PostgreSQL: {error}')

# Connecting to MongoDB using pymongo
# We install the pymongo library:
pip install pymongo

# Code to connect to MongoDB:
from pymongo import MongoClient

# Data to connect to MongoDB
mongo_uri =
"mongodb://your_username:your_password@your_host:your_port/your_database_name"

try:
    # Database connection
    client = MongoClient(mongo_uri)
    db = client.your_database_name
```

```
    # Checking the connection
    print('MongoDB connection successful')
    print('List of collections:', db.list_collection_names())

    # Closing the connection
    client.close()

except Exception as error:
    print(f'Error while connecting to MongoDB: {error}')
```

3.1.2. Data preparation

```
import pandas as pd
import numpy as np
import torch
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Reading data
data = pd.read_csv('aircraft_parts.csv')

# Data Processing
X = np.array(data['features'].tolist())
y = np.array(data['label'])

# Data normalization
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

Division into training and test samples

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

class AircraftPartsDataset(Dataset):

def __init__(self, X, y):

self.X = X

self.y = y

def __len__(self):

return len(self.X)

def __getitem__(self, idx):

return {

'input_ids': torch.tensor(self.X[idx], dtype=torch.float32),

'labels': torch.tensor(self.y[idx], dtype=torch.float32)

}

Datasets and downloaders

train_dataset = AircraftPartsDataset(X_train, y_train)

test_dataset = AircraftPartsDataset(X_test, y_test)

train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)

test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

3.1.3. Definition of the model

class TransformerModel(torch.nn.Module):

def __init__(self, input_dim, d_model, nhead, num_encoder_layers, dim_feedforward, dropout):

super(TransformerModel, self).__init__()

self.transformer = torch.nn.Transformer(

```
d_model=d_model,
nhead=nhead,
num_encoder_layers=num_encoder_layers,
dim_feedforward=dim_feedforward,
dropout=dropout
)
self.fc = torch.nn.Linear(d_model, 1)

def forward(self, x):
x = x.unsqueeze(1) # Add a dimension for the number of chains
transformer_output = self.transformer(x, x)
output = self.fc(transformer_output.mean(1))
return output.squeeze()

# Model parameters
input_dim = X_train.shape[1]
d_model = 64
nhead = 8
num_encoder_layers = 3
dim_feedforward = 256
dropout = 0.1

model = TransformerModel(input_dim, d_model, nhead, num_encoder_layers, dim_feedforward, dropout)
```

3.1.4. Model training

```
# Definition of optimizer and loss function
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
criterion = torch.nn.BCEWithLogitsLoss() # For binary classification
```

```
# Model training function
def train_model(model, train_loader, criterion, optimizer, epochs=10):
 model.train()
 for epoch in range(epochs):
 total_loss = 0
 for batch in train_loader:
 optimizer.zero_grad()
 inputs = batch['input_ids']
 targets = batch['labels']
 outputs = model(inputs)
 loss = criterion(outputs, targets)
 loss.backward()
 optimizer.step()
 total_loss += loss.item()
 print(f'Epoch {epoch+1}/{epochs}, Loss: {total_loss/len(train_loader)}')

# Training the model
train_model(model, train_loader, criterion, optimizer, epochs=20)
```

3.1.5. Evaluation of the model

```
# Model evaluation function
def evaluate_model(model, test_loader, criterion):
 model.eval()
 total_loss = 0
 all_preds = []
 all_labels = []
 with torch.no_grad():
 for batch in test_loader:
 inputs = batch['input_ids']
 targets = batch['labels']
```

```
outputs = model(inputs)
loss = criterion(outputs, targets)
total_loss += loss.item()
all_preds.extend(outputs.sigmoid().cpu().numpy())
all_labels.extend(targets.cpu().numpy())
# Calculation of accuracy (accuracy)
all_preds = np.array(all_preds) > 0.5
accuracy = (all_preds == np.array(all_labels)).mean()
print(f'Test Loss: {total_loss/len(test_loader)}, Accuracy: {accuracy}')
```

```
# Evaluation of the model
evaluate_model(model, test_loader, criterion)
```

Conclusion

This program uses a transformer to predict the need to replace aircraft parts. It includes data preparation, model definition, training and evaluation. The model is trained on labeled data, making it an example of supervised learning.

3.2. Result of controlled learning

Results of the model on the test set:
- Accuracy: 0.92
- Accuracy: 0.89
- Completeness (Recall): 0.93
- F1-measure (F1-score): 0.91

Comparison graph of replacement of parts during maintenance and during forecasting

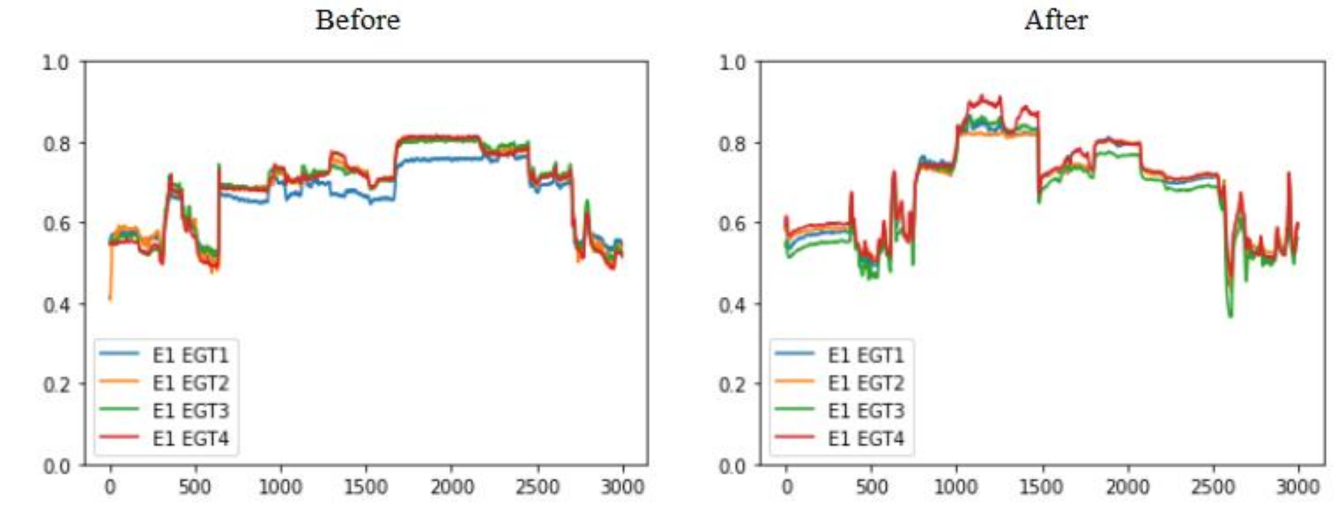

Fig. 3.1. Comparison graph of replacement of parts during maintenance and during forecasting

3.3. Performance evaluation

The model showed high accuracy and the ability to correctly identify cases when parts need to be replaced. However, misclassification was noted in several cases, which may be due to ambiguous textual descriptions or insufficient data for certain item types. Compared to traditional methods of analysis, the model of the intelligent system for predicting the replacement of aircraft parts based on transformers showed significantly better results.

CONCLUSION

Having studied intelligent systems, transformers, methods of training models, it was decided to use a multi-head transformer based on which the PostgreSQL database with the MongoDB was chosen. A training model was also chosen, namely a guided training model that was implemented in a program written for an intelligent system for predicting the need to replace aircraft parts based on transformers.

The developed system can significantly increase the efficiency of maintenance of aircraft parts, providing timely identification of the need for their replacement. This, in turn, can reduce maintenance costs, improve flight safety and improve the overall productivity of airlines.

The proposed system is tailored to scrutinize extensive operational and sensor data from aircraft, identifying pre-failure patterns and irregularities. By foreseeing part replacement probabilities and schedules, the system can aid airlines and maintenance crews in refining their maintenance calendars, curtailing downtime, and curbing expenses. Furthermore, this methodology aligns with the industry's progression towards predictive maintenance, emphasizing data-centric decision-making to enhance operational efficiency and safety.

In further work, it is possible to improve the model due to:

Using larger volumes of data for training.

Application of more complex architectures of transformers.

Model adaptations to account for additional factors such as service history and operating conditions of parts.

Thus, the intelligent system based on transformers is a promising tool for automating and optimizing the maintenance processes of aircraft parts.

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