In [3]:

```
from IPython.display import Image
from IPython.core.display import HTML
transformerarch=Image(url= "https://machinelearningmastery.com/wp-conte
```

## PreRequisite

Temperature-checking - how many of these concepts are we not familiar with?

1. Introduction to Machine Learning: ML, Supervised/Unsupervised;
2. Deep Learning (Basics): Neural networks, activation functions, backpropagation, gradient desent;
3. Convolutional Neural Networks: CNN & application in CV tasks;
4. Recurrent Neural Networks (RNNs): Basics, LSTM and GRU & usage in sequence data;
5. Intro to NLP: Overview of NLP - tokenization, word embeddings, sentiment analysis;
6. Seq2Seq models: how they work and their role in tasks like machine translation;
7. Attention Mechanism: Attention, Significance in transforming sequences;
8. Transformers and BERT

# Lecture Overview

# Lecture Overview

1. **Introduction to LLMs**: What LLMs are and why they're important
2. **Training LLMs**: On LLM's training including challenges and techniques involved
3. **Understanding GPT Architecture**: Understand GPT architecture used in LLMs.
4. **Fine-tuning Large Language Models**: Concept of fine-tuning and its application in LLMs.
5. **Applications of LLMs**: Examine real-world applications of LLMs within various use cases.
6. **Evaluating LLMs**: Learn about different metrics and methods and their *caveats* to evaluate the performance of LLMs.
7. **Bias in LLMs**: Discuss the potential for bias in LLMs and how to mitigate it.
8. **Limitations and Future of LLMs**: Discuss the current limitations of LLMs and future research directions.
9. **Hackathon-related refreshers**: Stochastics of time seires, API-based call of LLMs and Graphical Programming Interface that requires little-to-zero coding

# Introduction to LLMs and how they are trained

A type of ML model designed to understand, generate and converse in human language, 'large' due to the vast number of parameters.

- Ability to generate human-like texts
- Patterns in data used to train the model learnt allows the models to generate text based on received inputs
- Rule of thumb: 7B parameters takes one sota GPU to run, i.e. 13B takes two, etc.
- LLMs can perform natural language processing (NLP) tasks, note LLM ≠ NLP model
- OpenAI first released GPT-1 in 2018, and GPT 3 in 2020, where terrabytes of data were used to train these models

# Let’s see some LLMs in action

## Architecture of LLM

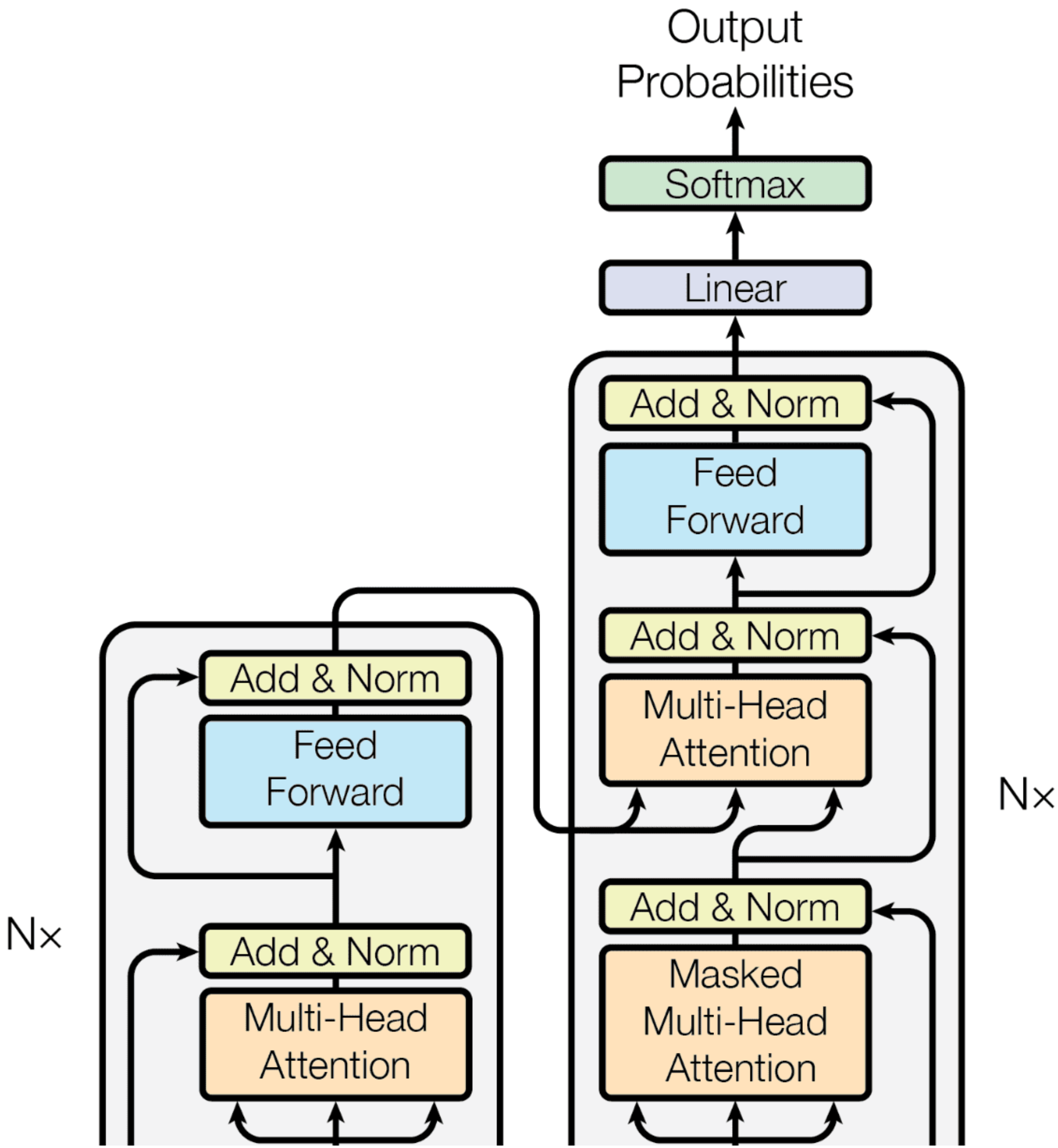
'Attention is All you Need', seminal paper on the most commonly used architecture known as **transformer** was first proposed, revoluntionized the field of NLP.

- Transformers are based on the **attention** mechanism, which allows the model to better associate words w.r.t. their positions, of primarily two types:
  - self-attention
  - multi-head attention
- Transformer = **encoder** (input) + **decoder** (Output)

In [4]:

```
transformerarch
#For those more keen on looking at the two components - note that GPT-3
```

Out[4]:



Output
Probabilities
Softmax
Linear
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Add & Norm
Masked
Multi-Head
Attention
Add & Norm
Feed
Forward
Nx
Add & Norm
Multi-Head
Attention

# Architecture of LLM - Transformer Layer Types

1. Self-Attention Layer: Scaled Dot-Product Attention
    - Allows model to focus on different parts of the input sequence when producing an output.
        - e.g. "The cat, which already ate...., was full." can prioritize "The cat" with "was full" before "already ate";
2. Position-wise Feed-Forward Layer
    - Fully-connected feed-forward network that is applied to each position separately and identically, each consists two linear transformations with a ReLU activation in between;
    - Used to sequentially process the output of the self-attention layer, appying the same learnt weights at every position;
3. Output layer
    - Linear layer followed by a softmax function, transforms the final hidden states to predictions for the next word in the sequence for each possible word in the vocabulary.

# Architecture of LLM - Data Handling by GPT Models

## Tokenization

Process of converting sequence of text into a sequence of tokens - a (part of) word. *Byte Pair Encoding* platform.openai.com/tokenizer

## BPE

- subwod tokenization method,
    - starts by splitting text into individual characters and
    - iteratively merges the most frequently adjacent pair of symbols.
- helps handle out-of-vocabulary words and makes the model more robust to spelling errors and variations

## Sequence length

# Architecture of LLM - Implementation and deployment of GPT

## Implementation

- Unlikely going to have retraining schedules.
- May require initial fine-tuning or tweaking OR
- Vanilla
- GPT-in-general: Implemented with Tensorflow or PyTorch: efficient, GPU-accelerated operations

## Deployment Process

- Models needs to reside on robust hardware or cloud-based solutions: consider numerous simultaneous requests
- Typically involves API-calls made to request services from models deployed on network
- Requests (e.g. text generation, text-completion) are handled and responses sent back

# Architecture of LLM - Back to the SOTA models

GPT-3, GPT-J, etc.: An **autoregressive, decoder-only transformer model** designed to solve natural language processing (NLP) tasks by **predicting** how a piece of text will continue.

This is different from traditional encoder-decoder transformer models like BERT where the inputs are first encoded and thrown together at the model as a whole when making the prediction.

GPT-3-like decoder-only models puts more emphasis on the more recent inputs, maknig the prediction continuously being more relevant with the more recent information.

- Advantage of decoder-only architecture:
    - Simplicity: easier to train less computationally expensive
    - Good at generative tasks, producing contextually relevant text - model is built to generate output one token at a time;
- Advantage of encoder-decoder model:
    - Better at classification tasks - tasks where specific structure is needed, e.g. translation, summarization, particularly good when input information comes all at once

Note here these are just high-level benefits, YMMV with different use cases.

A few notes:

1. *Autoregressiveness equals no parallelized during inference*
2. *Autoencoder* models should be differentiated from encoder-decoder model:
    - the prior also has an encoder and a decoder but primarily serves the purpose of dimension-reduction and denoising, aka 'learning' the input while
    - the latter is designed to work in sequence-to-sequence tasks.
    - i.e. autoencoder's output is representation of its input
    - encoder-decoder is not just a reconstruction of the input

Tying this back to GPT-3 models (and its alikes): LLMs performs sequence-to-sequence tasks but puts more weights to more recent context, yet it still considers all previous tokens (history) to predict the upcoming token.

# Architecture of LLM - Generative Pre-trained Transformer aka OpenAI's proposal

1. GPT-1: Improving Language Understanding by Generative Pre-training" in June 2018. 12 transformer layers and 117m parameters;
2. GPT-2: Released in 2019, has 1.5B parameters, text can become indistinguiashable to text written by humans;
3. GPT-3: Launched in 2020, (disclosed) largeset variant at 175B parameters, generate coherent and contextually relevant passages of text, introduction of 'few-shot learning'.
    - translation
    - Q&A
    - Writing creative contents like poems and stories
4. GPT-4: Released in 2023, no. of parameter undisclosed, still known as the most powerful LLM that has been released;

GPT-3.5: sub-class of GPT-3 first released in Apr. 2022, leading to '**chatGPT**' in Nov. 2023.

# Applications of LLMs: Examine real-world applications of LLMs within various use cases.

- Chatbots: User intention and logic. Short back-and-forth limits the need for larger context window
- Script-writing: Hollywood on strike for a reason.

Evaluating LLMs: Learn about different metrics and methods and their caveats to evaluate the performance of LLMs. Bias in LLMs: Discuss the potential for bias in LLMs and how to mitigate it. Limitations and Future of LLMs: Discuss the current limitations of LLMs and future research directions. Hackathon-related refreshers: Stochastics of time seires, API-based call of LLMs and Graphical Programming Interface that requires little-to-zero coding

# Common Selection Strategies seen in LLM Application Development

Inference-time paramters that affect how tokens are generated by a LLM.

- Temperature: Deterministic to Creativity
    - Randomness of model output (0-1)
    - When set to 0, outputs is completely reproducible
    - When set to 1, model is more random, aka has more 'creative' outputs
- Top_K Sampling: Number of top tokens considered for best next word
    - limits us to a certain number of the top tokens to consider
- Top_P Sampling: Probability threshold
    - Recall the models are statistical in nature, use a threashold of probability, e.g. 90%
- Token length & Max tokens: Number of tokens fed to/generated by LLMs
    - Relevant due to the amount of time of solution generated
    - Also relevant to costs (Most close models charge by # of tokens used)

# Break

# Quick Recap

- Talked about onboarding to GCP and some high-level contents w.r.t. how LLMs work
- In particular touch upon the following concept:
    - Temperature
    - top_N
    - probabilities
- Now switching gear back to the learning series, we will talk about Application of LLMs today.
- Let's begin with the five common pillars recognized by OpenAI (or GPT-4 itself)

# Key Applications Recognized

1. Content Creation
    - write articles
    - generate ideas/scripts for writers
    - **creativity and fluency**
2. Conversation Agents:
    - chatbot/virtual assistant (Pershin X)
    - Human-like **interaction**
    - *Can answer queries, provide recommendations and hold conversations*
3. Translation:
    - not explicitly trained to do this
    - *Can handle various languages nonetheless*
4. Education
    - Tutor various subjects
    - *Can provide explanations, stimulate creative thinking*
5. Programming Help: CoPilot
    - *Can generate code snippets and assist with debugging*

# Limitations and Ethical Considerations of Large Language Models

- Limitations
    - Understanding vs. Pattern Matching
    - Sensitivity to Input Phrasing
    - Verifiability of information: generating plausible-sounding but incorrect/nonsensical information.
        - no inherent way to verify accuracy of the information it generates
        - **but doesn't 'grounding' solve this?**
- Ethical Considerations
    - Bias in Training Data
        - gender, racial cultral biases and more
    - Misuse of Technology
        - deepfake text for nefarious purposes
    - Social/Environmental Impact
        - training of LLM is very energy intensive ad requires significant amount of computational resources
        - Role of human/smart copiers' role in RLHF

# How does 'Grounding' work?

- What is 'grounding':
  - Refers to the concept of connecting the LLM with real-world concrete data or knowledge source
  - May include:
    - linking to specific databases,
    - using factual knowledge graphs, or
    - providing the model with access to up-to-date information on the internet.
- MSFT once claimed it will resolve most of our concerns/problems.
  - RFP PoC/Pilot
  - Chat with your PDF(s) demo
- **Verfiability issue is more than just factual grounding.**

# Why doesn’t ’Grounding’ work?

- Grouding will improve accuracy of responses and keep them factual
- Creates a form of question-answering system that performs semantic search over a known corpus of documents
- Some points to consider:
    1. Model interpretation (temp=0, aka model outputs more deterministic): model understanding ≠ human understanding;
    2. Accuracy within context: errors acn arise from:
        - biases/inaccuracies in training data,
        - misinterpretation of context,
        - limitations in the model's understanding of complex language structures;
    3. Handling Ambiguity: question or context is ambigous, the model might struggle to provide an accurate and relevant answer.

**’Grounding’ may improve verifiability of a model’s response, it won’t eliminate the issue.**

# Mitigating LLM Risks

- Fine-tuning on specific datasets: improve behavior for **specific** applications
  - Refers to the concept of connecting the LLM with real-world concrete data or knowledge source
  - May include:
    - linking to specific databases,
    - using factual knowledge graphs, or
    - providing the model with access to up-to-date information on the internet.
- MSFT once claimed it will resolve most of our concerns/problems.
  - RFP PoC/Pilot
  - Chat with your PDF(s) demo
- **Verfiability issue is more than just factual grounding.**

# Quick Re-Cap on what we discussed

- Basics of LLMs
    - What they are and how they are trained
- Architecture of GPT models (Decoder-only ones started by OpenAI)
    - Transformer architecture
    - Decoder-only vs. encoder-decoder architectures
- Implementation and Deployment
    - APIs
    - Real-world usage and applications we built
- Limitations and Concerns
    - Lack of human-intent-understanding capability
    - Inability to provide verification
    - Proneness to biases
- Implications of LLMs
    - Wide-ranging capabilities and applications of these models
    - Potential risks and concerns
    - Strategies to mitigate these risks

# Quick Re-Cap on what we discussed - Synthesized

- Basics of LLMs
  - Generative Pre-Trained (on large text corpora) Models
- Architecture of GPT models (Decoder-only ones started by OpenAI)
  - Decoder-only, no parallization
- Implementation and Deployment
  - OpenAI & Google: APIs
  - Open-Source models: Google Colab, i.e. local/remote GPUs(CLI)
- Limitations and Concerns
  - It doesn't 'understand' prompts and human intentions
  - But can sound very convincing as trained on great writing examples - is it a better writer?
- Implications of LLMs
  - Different learning experiences
  - Revolutionize coding experience (CoPilot)
  - Further reduction of workforce (e.g. Customer Service, call center reps)

# Some Options to test/understand LLMs

- Langflow
- Flowise