# Generative AI Pipeline

1. Data Acquisition

* Available Data(csv,text,pdf, docx,xlsx or others)
* Other Data (DB, internet, API, web scrapping)
* No Data (create your own data) 🡪 LLM to generate Data  
  Note: if you have less data then you perform data augmentation,  
  ex: Replace with synonyms (I am Data Scientist 🡪 I am AI engineer)
* **BIGRAM FLIP**I am Bappy 🡪 Bappy is my name
* **BACK TRANSLATE**
* **ADDITIONAL DATA/NOISE**I am a data Scientist. I love my job.

1. Data Preparation/ Preprocessing

* CLEANUP: HTML,EMOJI, SPELLING CORRECTION
* BASIC PRE-PROCESSING:  
  Tokenization (a) SENTENCE b) WORD
* OPTIONAL PREPROCESSING –( Stop word removal,  
   steaming(less used today), Lemmatization(more used)  
  **steaming 🡪 play, played and playing 🡪 root form Play**
* Lemmatization
* PUNCTUATION REMOVAL
* LOWER CASE
* LANGUAGE DETECTION

ADVANCE PRE\_PROCESSING

* Part of Speech Tagging
* Parsing
* Coreference resolution

1. Feature Engineering

TEXT VECTORIZATION ( TFIDF, Bag of words, word2vec, one hot encoding, transformers models)

1. Modeling

Choose between open source and paid one

1. Evaluation

Intrinsive Evaluation (GEN AI Engineer)

Extrinsic Evaluation – After doing the deployment

1. Deployment
2. Monitoring and model updating/retraining

## Text Representation

1. What is feature extraction from text/images? Edges patterns
2. Why we need it? Numbers or vectors
3. Why it is so difficult ? (Test data)
4. What is the core idea?
5. Some techniques?

Example audio

A diagram of a frequency response

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Audio and videos can have fixed data as table but for text data is very variable (that is input size is variable).

Ways to solve it

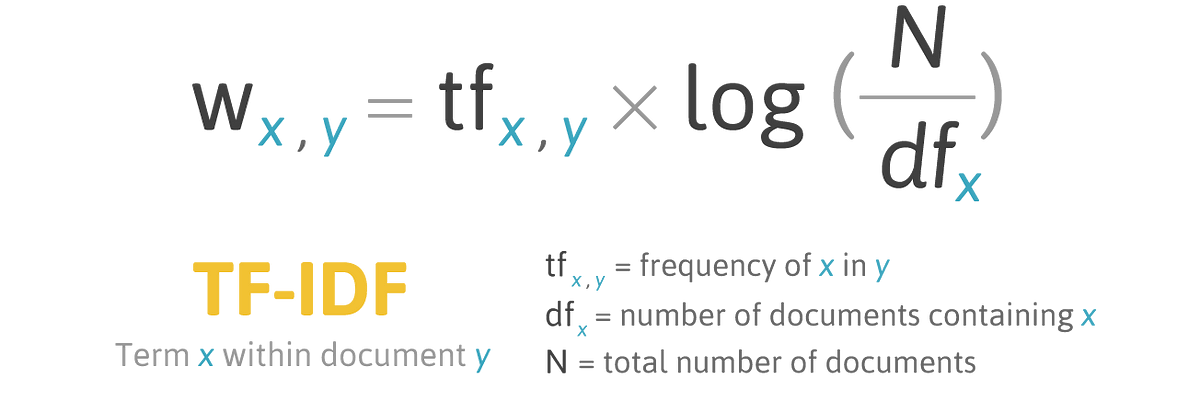
1. One- hot encoding
2. Bag of words

One-Hot Encoding 🡪 Drawbacks 🡪 Sparcity 🡪 No fixed size 🡪 out of vocabulary issue 🡪 Does not capture Semantic meaning 🡪 Don’t follow

Bag of Word  
Other methods TFIDF, Word2Vec, And Transformer models

N-Gram- It is a concept were you consider N-consecutive elements as 1 unit/token

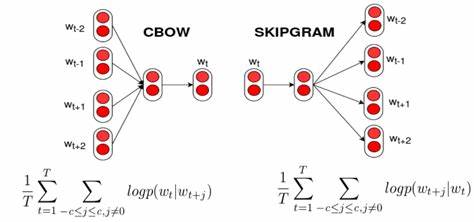
TF-IDF- works on one statistical Equation



TF-IDF🡪 Drawback 🡪 Cannot contain semantic information

**Word2Vec**

Word2Vec uses 2 kinds of architecture CBOW and SKIPGRAM



**ZERO-Shot Learning**

"The approach using a single command to get an LLM to take on a behavior is called Zero Shot Learning"

**Few Shot Learning**  
*In addition, to just providing an instruction it can be helpful to show the model what you want by adding examples this is called few shot learning because we showed the model a few examples*

**Like here is a prompt for translating from English to French**  
*First, we provide an instruction as shown below*  
***Convert the text from English to French***  
*Then we give some examples establishing the text pattern*

**Few Shot Learning**

***Convert the text from English to French*** ← *Instruction*

**Examples Establishing the Text Pattern:**

* **Peppermint:** menthe poivrée
* **Desert cactus:** Cactus du désert
* **Potato:** pomme de terre
* **Lipstick:** Rouge à lèvres
* **Orange Juice:** du jus d'orange
* **Sparkling water:** Eau gazeuse

**How ChatGPT was trained?**

Internally using a LLM which is gpt-3.5 or gpt-4  
It has trained on a large amount of data which is available all over the internet.

1. Generative pre-training
2. Supervised fine-tuning
3. Reinforcement learning

A screenshot of a computer

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**Stage 1 - Generative Pre-Training**

* **Input:** Internet text data + Document text data
* **Description:**  
  A base GPT model is trained on a large corpus of text data from the internet using the Transformer architecture.

"This base model thingy (GPT) was trained on a bunch of stuff from the Internet for a whole bunch of different things by using the Transformer Architecture."

**Stage 2 - Supervised Fine Tuning (SFT)**

* **Description:**  
  Human AI trainers have conversations where they act as both the user and the assistant to fine-tune the model.

"Next, with the human AI trainers, you get to have conversations where they play both sides – you and an AI assistant."

**Stage 3 - Reinforcement Learning through Human Feedback (RLHF)**

* **Description:**  
  The model is optimized further by comparing responses and training it using a reward model.

"Next, let’s take the model to the next level by optimizing it even more with Reinforcement Learning by training it against a reward model."

A screenshot of a computer screen

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**🔶 Title: Generative Pre-Training**

**🧠 Process Overview:**

* **Input Sources:**
  + 🌐 Internet text data
  + 📄 Documents text data
* **Model Architecture:**
  + 🔷 Transformer
* **Output:**
  + ➡️ **Base GPT Model**

**🔍 Key Insights:**

* The Transformer is trained on massive text corpora to **create a base GPT model**.
* This base model captures language structure and general knowledge.

**🔧 What it can do (Reality):**

* ✅ Text Summary
* ✅ Sentiment Analysis
* ✅ Sentence Completion
* ✅ Translation

**🎯 What we want it to do (Expectation):**

* 🗨️ **Chat and conversation**

A diagram of a process flow

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**🔶 Title: Supervised Fine-Tuning (SFT)**

**🧠 Process Overview:**

1. **Crafted Conversations**
   * A **human agent** (acting like an ideal AI assistant) creates **ideal responses** to prompts (requests).
   * Example:
     + Request 1 → Ideal Response 1
     + Request 2 → Ideal Response 2
     + Request 3 → Ideal Response 3
2. **SFT Training Data Corpus**
   * These prompt-response pairs are collected as training data.
   * The conversation history and ideal next responses are visually marked.
3. **Training**
   * The **Base GPT model** is fine-tuned using this corpus.
   * The **Stochastic Gradient Descent (SGD)** algorithm is used for optimization.
   * Output: **SFT ChatGPT Model**

Human Agent → Prompt-Response Pairs → Base GPT Model → SGD → Fine-Tuned (SFT) ChatGPT Model

This stage helps the model learn **how to respond more helpfully and safely**, forming the foundation for human-like dialogue.

A diagram of a project

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**🔶 Title: Reinforcement Learning through Human Feedback (RLHF)**

**🧠 Process Overview:**

1. **Start with the SFT-trained ChatGPT Model**
   * It generates multiple **alternate responses (A–D)** to a given **user request**.
2. **Human Agent Evaluation**
   * Human evaluators **rank the responses** based on quality (e.g., helpfulness, correctness, harmlessness).
   * Example Ranking:
     + Alt Response B > A > D > C
3. **Reward Model Training**
   * These rankings train a **Reward Model** that learns to assign scores to responses:
     + Score\_A, Score\_B, Score\_C, etc.
   * Input: Conversation history + response
4. **Policy Optimization**
   * This reward model is used to fine-tune the model using **Reinforcement Learning**, guiding it to prefer higher-ranked (better) responses.

A diagram of a diagram

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# HUGGINGFACE (Transformers)

* 1. Pipeline
  2. NLP tasks
  3. Tokenization
  4. Dataset and spaces
  5. FineTuning LLM with huggingFace
  6. Project Implementation

2 procedure explained  
1) Taking pre-trained model from hugging face.  
2) Fine- tune model (banking data or other kind of specialized data)

**ChatCompletion API and Completion API**

* **Completion API**: Hooks you up with text completions from a single prompt.
* **Chat Completion API**: Nails it in the chat game, keeping the conversational flow intact

**🧠 Key Differences**

* **Completion API**:

*Hooks you up with text completions from a single prompt.*

* + Designed for **one-shot** or **single-turn** tasks.
  + Input: a block of text.
  + Output: continuation of that text.
  + Example use: Autocomplete, summarization, code generation.
* **ChatCompletion API**:

*Nails it in the chat game, keeping the conversational flow intact.*

* + Structured for **multi-turn** interactions (like a chatbot).
  + Uses a list of messages with roles: user, assistant, and system.
  + Maintains **conversational context** across multiple inputs.

**Function Calling in OpenAI**

**JSON**

Model

OpenAI   
API

JSON

Function Calling

**OPEN AI supports third party software**

**PROMPT Engineering**

Best Practices to design a prompt

* Clear instruction
* Adopt a persona
* Specify the format
* Avoid leading the answer
* Limit the scope

Types of Prompting

* Zero-shot prompting
* Few-shot prompting

# Vector Database

**Unstructured data as Text**

**Embedding model**

| **Feature** | **King** | **Queen** | **Man** | **Woman** | **Monkey** |
| --- | --- | --- | --- | --- | --- |
| Gender | 1 | 0 | 1 | 0 | 1 |
| Wealth | 1 | 1 | 0.5 | 0.3 | 0 |
| Power | 1 | 0.7 | 0.5 | 0.2 | 0 |
| Weight | 0.8 | 0.5 | 0.7 | 0.5 | 0.3 |
| Speed | 1 | 1 | 1 | 1 | 0 |

king ⇒ [1, 1, 1, 0.8, 1]

queen ⇒ [0, 1, 0.7, 0.5, 1]

man ⇒ [1, 0.5, 0.7, 0.7, 1]

→ OpenAI Embedding → GPT model

→ Hugging Face Embedding → Open source LLM

→ Llama 2 Embedding 🡪 Meta

→ Google PaLM Embedding 🡪 Google

A diagram of a diagram

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In the context of **vector embeddings**, a **vector index** is a data structure that enables efficient storage, retrieval, and similarity search of high-dimensional embedding vectors.

**Explanation based on the image:**

1. **Input**:
   * You start with **unstructured data** (e.g., text, images, audio).
2. **Embedding Generation**:
   * This data is passed through a model that converts it into **embedding vectors**—numerical representations in high-dimensional space.
   * For example:  
     "document A" → [0.4, 0.7, 0.9, 0.1, 0.5, ...]
3. **Vector Index**:
   * These embedding vectors are stored in a **vector index**, which assigns a unique identifier to each vector and stores them for **fast similarity search**.
   * This index enables you to:
     + **Quickly find nearest neighbors** (e.g., using cosine similarity or Euclidean distance).
     + **Perform semantic search**, where similar meaning returns similar vectors.
4. **Use Case**:
   * When you query something new, you embed the query and then use the vector index to find the most similar stored embeddings (i.e., similar documents, images, etc.).

**Key Benefits of Vector Indexes:**

* **Speed**: Handles large-scale search efficiently.
* **Scalability**: Can manage millions of embeddings.
* **Versatility**: Used in search engines, recommendation systems, and chat-based retrieval (RAG pipelines).

**Tools for Vector Indexing:**

* **FAISS** (Facebook AI Similarity Search)
* **Pinecone**
* **Weaviate**
* **Milvus**
* **Annoy** (Approximate Nearest Neighbors)

A diagram of data processing

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The image lists **use cases of Vector Databases (Vector DB)** as follows:

1. **Long-Term memory for LLMs**
   * Store and retrieve contextual knowledge to extend language model capabilities.
2. **Semantic Search**
   * Enables search **based on meaning**, not just exact keyword matches.
3. **Similarity Search**
   * Works across various modalities: **Text, Images, Videos, Audios** to find related items.
4. **Recommendation engine as well**
   * Powers personalized suggestions by comparing user/item embeddings.