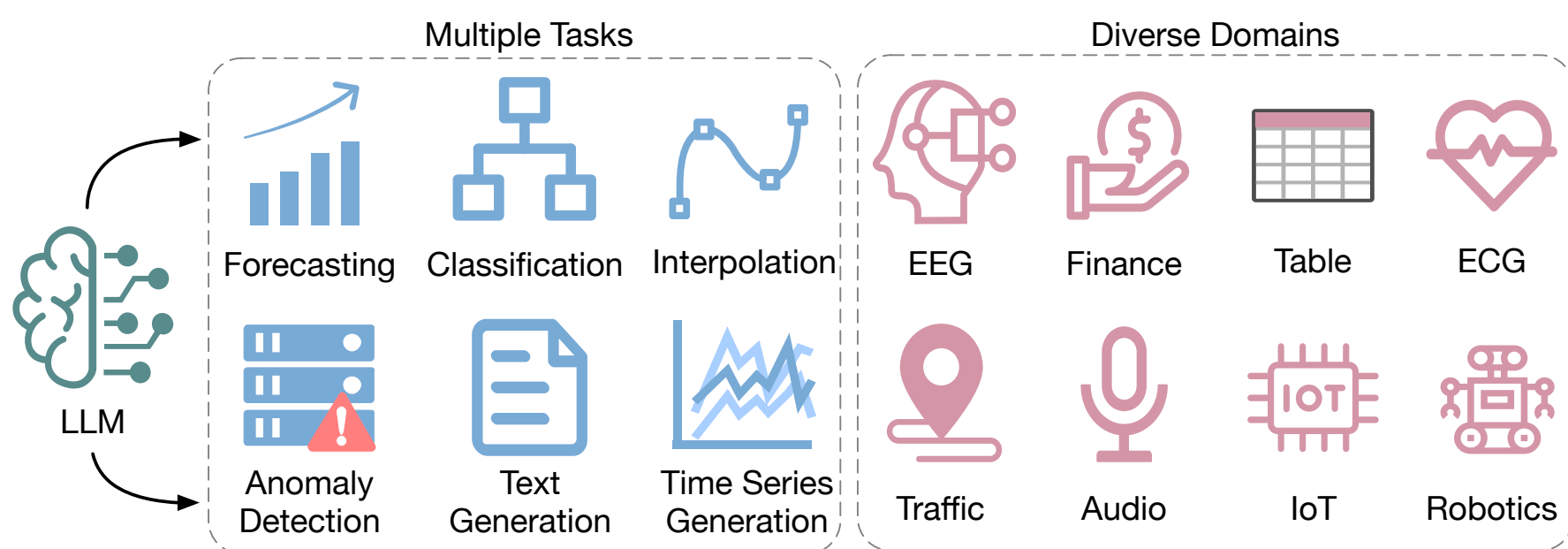


## Introduction

- LLMs have significantly revolutionized NLP and CV domains.
- How can LLMs benefit time series analysis?



- Key challenge
  - How to bridge the modality gap between LLMs trained on *discrete textual data* and *continuous numerical time series*?

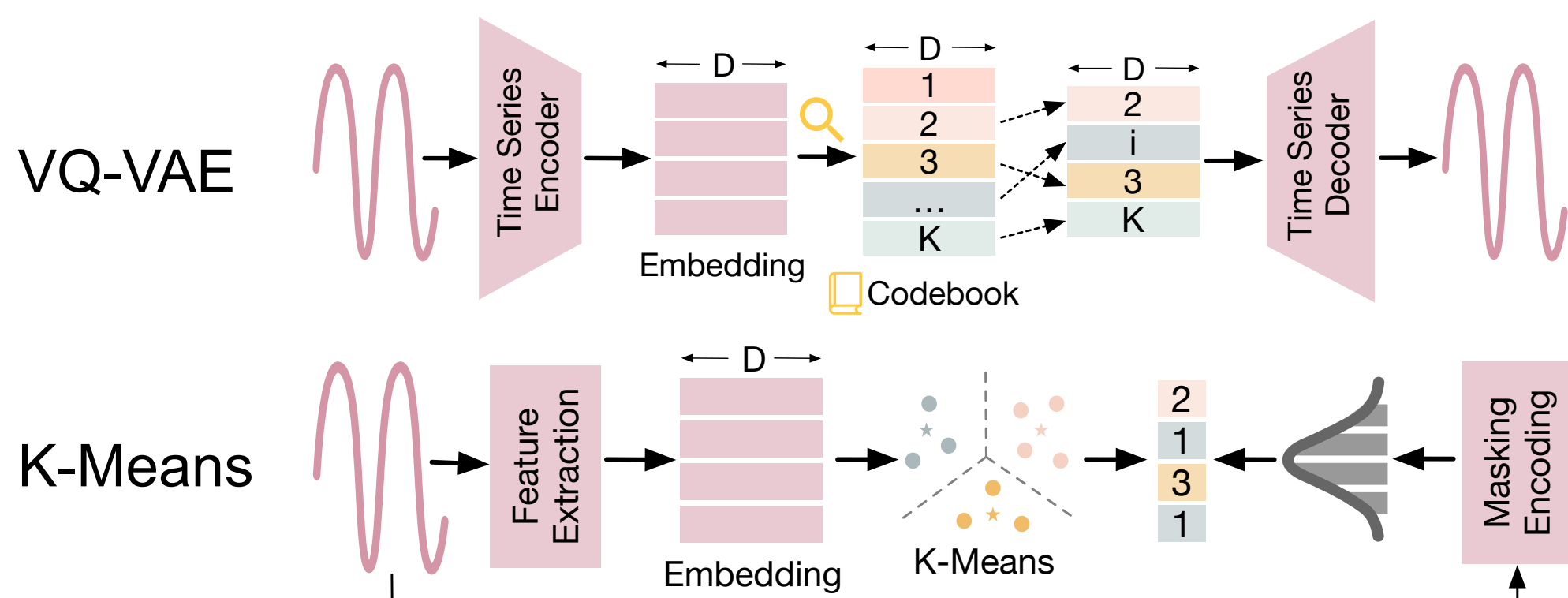
## Taxonomy

- If we outline typical LLM-driven NLP pipelines in five stages
  - Input text, tokenization, embedding, LLM, output
- Then each category of our taxonomy targets one specific stage in this pipeline

- Prompting (Input Stage)**
  - Number-agnostic tokenization
  - Number-specific tokenization

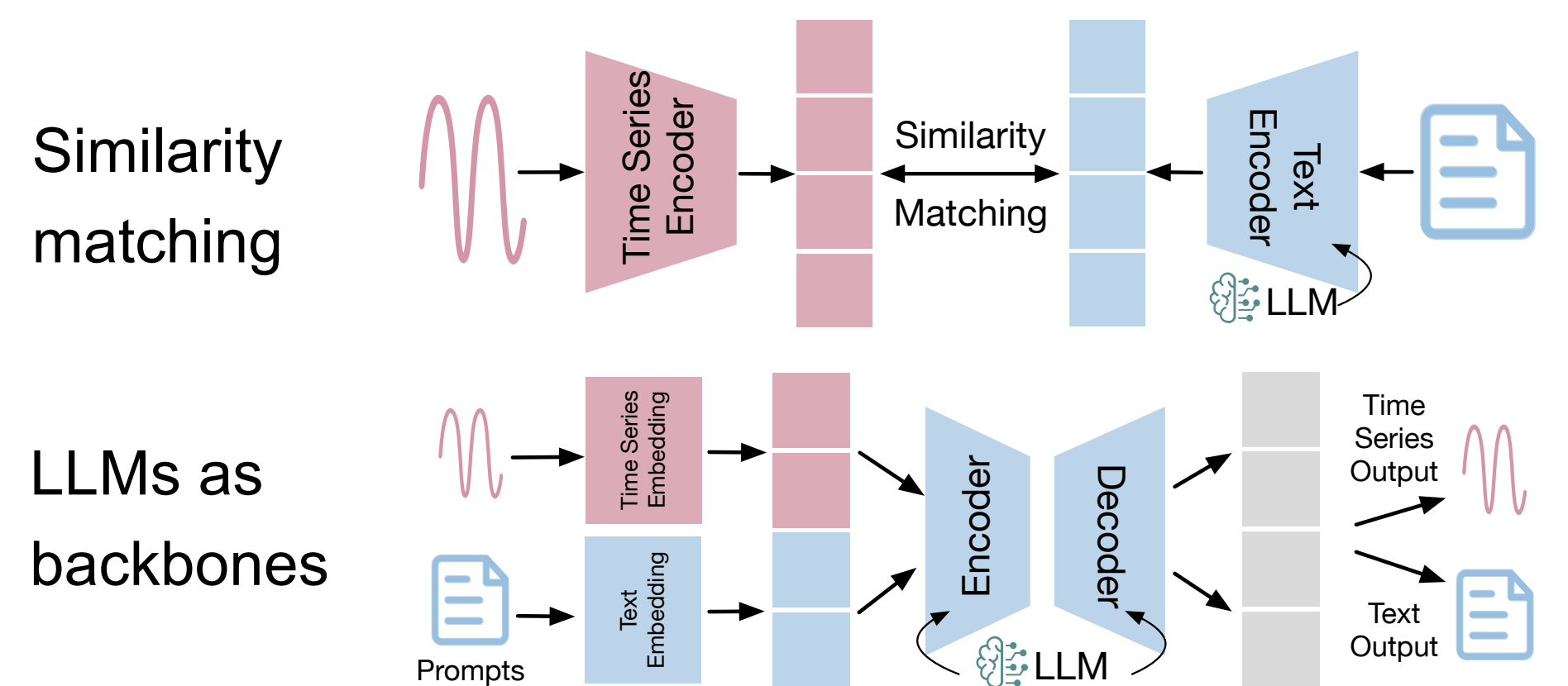
| Method                           | Example  |
|----------------------------------|--|
| PromptCast [Xue and Salim, 2022] | "From $\{t_1\}$ to $\{t_{obs}\}$ , the average temperature of region $\{U_m\}$ was $\{x_t^m\}$ degree on each day. What is the temperature going to be on $\{t_{obs}\}$ ?" |
| Liu et al. [2023d]               | "Classify the following accelerometer data in meters per second squared as either walking or running: 0.052,0.052,0.052,0.051,0.052,0.055,0.051,0.056,0.06,0.064"          |
| TabLLM [Hegselmann et al., 2023] | "The person is 42 years old and has a Master's degree. She gained \$594. Does this person earn more than 50000 dollars? Yes or no? Answer:"                                |
| LLMLTime [Gruver et al., 2023]   | "0.123, 1.23, 12.3, 123.0" → "1 2, 1 2 3, 1 2 3 0, 1 2 3 0 0"  |

- Quantization (Tokenization Stage)**
  - Discrete indices from VQ-VAE
  - Discrete indices from K-Means



## Aligning (Embedding Stage)

- Similarity matching
- LLMs as backbones



## Vision as Bridge (LLM Stage)

- Paired data, physics relationships, time series plots as images

## LLMs as Tools (Output Stage)

- Code, API call, text domain knowledge

## Comparison within the Taxonomy

| Method           | Subcategory        | Representative Works                               | Equations   | Advantages   | Limitations                        |
|------------------|--------------------|--|---|--|------------------------------------|
| Prompting        | Number-Agnostic    | PromptCast [Xue and Salim, 2022]                   | $y = f_{\theta}(\mathbf{x}_s, \mathbf{x}_t)$  | easy to implement; zero-shot capability                      | lose semantics; not efficient      |
|                  | Number-Specific    | LLMLTime [Gruver et al., 2023]                     |   |  |                                    |
| Quantization     | VQ-VAE             | DeWave [Duan et al., 2023]                         | $k_t = \arg \min_j \ g_{\phi}(\mathbf{x}_s)_t - \mathbf{c}_j\ _2$   | flexibility of index and time series conversion              | may require two-stage training     |
|                  | K-Means            | AudioLM [Borsos et al., 2023]                      | $\mathbf{k} = [k_i]_{i=1}^T, \mathbf{y} = f_{\theta}(\mathbf{k}, \mathbf{x}_t)$                                       |  |                                    |
|                  | Text Categories    | TDML [Yu et al., 2023]                             | $\mathbf{y} = f_{\theta}(g(\mathbf{x}_s), \mathbf{x}_t)$  |  |                                    |
| Aligning         | Similarity Match   | ETP [Liu et al., 2023a]<br>MATM [Han et al., 2022] | $\mathbf{y} = g_{\phi}(\mathbf{x}_s)$<br>$\mathcal{L} = \text{sim}(g_{\phi}(\mathbf{x}_s), f_{\theta}(\mathbf{x}_t))$ | align semantics of different modalities; end-to-end training | complicated design and fine-tuning |
|                  | LLM Backbone       | GPT4TS [Zhou et al., 2023a]                        | $\mathbf{y} = f_{\theta}(g_{\phi}(\mathbf{x}_s), \mathbf{x}_t)$   |  |                                    |
| Vision as Bridge | Paired Data        | ImageBind [Girdhar et al., 2023]                   | $\mathcal{L} = \text{sim}(g_{\phi}(\mathbf{x}_s), h_{\psi}(\mathbf{x}_v))$  | additional visual knowledge                                  | not hold for all data              |
|                  | TS Plots as Images | Wimmer and Rekabsaz [2023]                         | $\mathbf{y} = h_{\psi}(\mathbf{x}_s)$   |  |                                    |
| Tool             | Code               | CTG++ [Zhong et al., 2023]                         | $z = f_{\theta}(\mathbf{x}_t)$  | empower LLM with more abilities                              | optimization not end-to-end        |
|                  | API                | ToolLLM [Qin et al., 2023]                         | $\mathbf{y} = z(\mathbf{x}_s)$  |  |                                    |

## Datasets

- Internet of Things (IMU), healthcare (EEG, ECG), finance (stock), audio/music/speech

| Domain             | Dataset  | Size                                  | Major Modalities            | Task                               |
|--------------------|--|---------------------------------------|-----------------------------|------------------------------------|
| Internet of Things | Ego4D <sup>2</sup> [Grauman et al., 2022]          | 3, 670h data, 3.85M narrations        | text, IMU, video, audio, 3D | classification, forecasting        |
|                    | DeepSQA <sup>3</sup> [Xing et al., 2021]           | 25h data, 91K questions               | text, imu                   | classification, question answering |
| Finance            | PIXIU <sup>4</sup> [Xie et al., 2023b]             | 136K instruction data                 | text, tables                | 5 NLP tasks, forecasting           |
|                    | MoAT <sup>5</sup> [Lee et al., 2023]               | 6 datasets, 2K timesteps in total     | text, time series           | forecasting                        |
| Healthcare         | Zuco 2.0 <sup>6</sup> [Hollenstein et al., 2019]   | 739 sentences                         | text, eye-tracking, EEG     | classification, text generation    |
|                    | PTB-XL <sup>7</sup> [Wagner et al., 2020]          | 60h data, 71 unique statements        | text, ECG                   | classification                     |
|                    | ECG-QA <sup>8</sup> [Oh et al., 2023]              | 70 question templates                 | text, ECG                   | classification, question answering |
| Audio              | OpenQA-5M <sup>9</sup> [Gong et al., 2023]         | 5.6M (audio, question, answer) tuples | text, audio                 | tagging, classification            |
| Music              | MusicCaps <sup>10</sup> [Agostinelli et al., 2023] | 5.5K music clips                      | text, music                 | captioning, generation             |
| Speech             | CommonVoice <sup>11</sup> [Ardila et al., 2019]    | 7, 335 speech hours in 60 languages   | text, speech                | ASR, translation                   |

## Resources

## Paper

## Github

- Check out our paper and Github repo ([awesome-llm-time-series](#)) for more details!

