Chemical Science

ROYAL SOCIETY OF CHEMISTRY

EDGE ARTICLE

View Article Online
View Journal | View Issue

Check for updates

Cite this: *Chem. Sci.*, 2024, **15**, 10600

All publication charges for this article have been paid for by the Royal Society of Chemistry

Fine-tuning large language models for chemical text mining†

Wei Zhang,‡[ab] Qinggong Wang,‡[c] Xiangtai Kong,[ab] Jiacheng Xiong,[ab] Shengkun Ni,[ab] Duanhua Cao,[ad] Buying Niu,[ab] Mingan Chen,[aef] Yameng Li,[g] Runze Zhang,[ab] Yitian Wang,[ab] Lehan Zhang,[ab] Xutong Li,[ab] Zhaoping Xiong,[g] Qian Shi,[f] Ziming Huang,[h] Zunyun Fu*[a] and Mingyue Zheng *[abc]

Received 6th February 2024
Accepted 2nd June 2024

DOI: 10.1039/d4sc00924j

rsc.li/chemical-science

Extracting knowledge from complex and diverse chemical texts is a pivotal task for both experimental and computational chemists. The task is still considered to be extremely challenging due to the complexity of the chemical language and scientific literature. This study explored the power of fine-tuned large language models (LLMs) on five intricate chemical text mining tasks: compound entity recognition, reaction role labelling, metal–organic framework (MOF) synthesis information extraction, nuclear magnetic resonance spectroscopy (NMR) data extraction, and the conversion of reaction paragraphs to action sequences. The fine-tuned LLMs demonstrated impressive performance, significantly reducing the need for repetitive and extensive prompt engineering experiments. For comparison, we guided ChatGPT (GPT-3.5-turbo) and GPT-4 with prompt engineering and fine-tuned GPT-3.5-turbo as well as other open-source LLMs such as Mistral, Llama3, Llama2, T5, and BART. The results showed that the fine-tuned ChatGPT models excelled in all tasks. They achieved exact accuracy levels ranging from 69% to 95% on these tasks with minimal annotated data. They even outperformed those task-adaptive pre-training and fine-tuning models that were based on a significantly larger amount of in-domain data. Notably, fine-tuned Mistral and Llama3 show competitive abilities. Given their versatility, robustness, and low-code capability, leveraging fine-tuned LLMs as flexible and effective toolkits for automated data acquisition could revolutionize chemical knowledge extraction.

Introduction

Chemical text mining is a crucial foundation in chemical research. It creates extensive databases that provide access to physicochemical properties and synthetic routes for experimental chemists. Additionally, it accumulates rich data and insights for computational chemists to use for modelling and predicting. More than just extracting information from chemical texts, the rule-based transformation of chemical text is particularly interesting. For instance, synthetic procedures can be converted into action sequences[1,2] or programming languages.[3–5] This allows them to be understood and executed by robotics for automated syntheses.

However, converting structured data from intricate scientific literature is a challenging task, especially due to the complexity and heterogeneity of chemical language. As a result, a number of text-mining tools have been developed. For instance, ChemDataExtractor[6,7] was created to extract chemical entities and their associated properties, measurements and relationships from chemical documents, using unsupervised word clustering, conditional random fields, rule-based grammar and dictionary matching. ChemRxnExtractor,[8] a BERT-like model, was designed to extract the product and label associated reaction roles such as the reactant, catalyst, solvent, and temperature from paragraphs of synthesis experiments. Vaucher *et al.*[1,2] developed task-adaptive pre-trained transformers to convert the synthesis protocol paragraphs into action sequences. SynthReader[3] was built to convert literature syntheses to executable XDL formats, containing a series of domain-specific algorithms

[a] Drug Discovery and Design Center, State Key Laboratory of Drug Research, Shanghai Institute of Materia Medica, Chinese Academy of Sciences, 555 Zuchongzhi Road, Shanghai 201203, China. E-mail: myzheng@simm.ac.cn; fuzunyun@simm.ac.cn

[b] University of Chinese Academy of Sciences, No. 19A Yuquan Road, Beijing 100049, China

[c] Nanjing University of Chinese Medicine, 138 Xianlin Road, Nanjing 210023, China

[d] Innovation Institute for Artificial Intelligence in Medicine of Zhejiang University, College of Pharmaceutical Sciences, Zhejiang University, Hangzhou, Zhejiang 310058, China

[e] School of Physical Science and Technology, ShanghaiTech University, Shanghai 201210, China

[f] Lingang Laboratory, Shanghai 200031, China

[g] ProtonUnfold Technology Co., Ltd, Suzhou, China

[h] Medizinische Klinik und Poliklinik I, Klinikum der Universität München, Ludwig-Maximilians-Universität, Munich, Germany

† Electronic supplementary information (ESI) available. See DOI: https://doi.org/10.1039/d4sc00924j

‡ These authors contributed equally to this work.

with predefined rules. Historically, the focus has been on designing models and algorithms specific to certain tasks, requiring extensive domain knowledge and sophisticated data processing. These tools, challenging to adapt for diverse extraction tasks, often require complementary collaboration to manage complex information extraction tasks, thus limiting their versatility and practicality.

Recently, large language models (LLMs), represented by ChatGPT released in November 2022, have shown the potential for Artificial General Intelligence (AGI). LLMs, such as GPT-3.5 and GPT-4, can generate logical insights or content that meets requirements based on human instructions. We are entering a new era where AGI and medicinal chemists might work together. There have been some assessments of ChatGPT's chemistry capabilities, including tasks like synonym transformation, property prediction, retrosynthesis, and molecule design.[9–11] However, LLMs tend to “hallucinate”, meaning they generate unintended text that misaligns with established facts and real-world knowledge.[12,13] Moreover, objectively evaluating the results of open-ended questions remains a significant challenge.

At this juncture, LLMs may still find it difficult to accurately answer factual and knowledge-based questions. However, using LLMs for knowledge extraction tasks should greatly alleviate hallucination and fully leverage their powerful text comprehension and processing capabilities, making them promising universal tools for chemical text mining. For instance, Zheng *et al.*[14] used prompt engineering to guide ChatGPT in extracting information about metal–organic framework (MOF) synthesis. Patiny *et al.*[15] tried to use ChatGPT to extract FAIR (Findable, Accessible, Interoperable, Reusable) data from publications. However, their approach of using LLMs simply based on prompt engineering tends to achieve poor performance in exact accuracy. According to the biomedical benchmark study by Chen *et al.*,[16] ChatGPT performed significantly worse on biomedical text mining compared to existing models. These findings seem to contradict the common belief in the LLMs' superior comprehension abilities. Either way, LLMs have limitations due to their model architecture and memory, including a maximum length of prompt tokens. Besides, human expressions can be ambiguous, incomplete, vague, and difficult to refine. Outputs may not strictly adhere to formatting requirements, leading to misunderstanding and poor performance in mining complex text, such as patents or scientific literature. Therefore, zero-shot or few-shot prompts are often insufficient to address the diversity of scenarios and cannot guarantee the quality of extracted data.

In this study, we extensively explored the effectiveness of fine-tuning LLMs on five challenging tasks in chemical text mining: compound entity recognition, reaction role annotation, metal–organic framework (MOF) synthesis information extraction, nuclear magnetic resonance spectroscopy (NMR) data

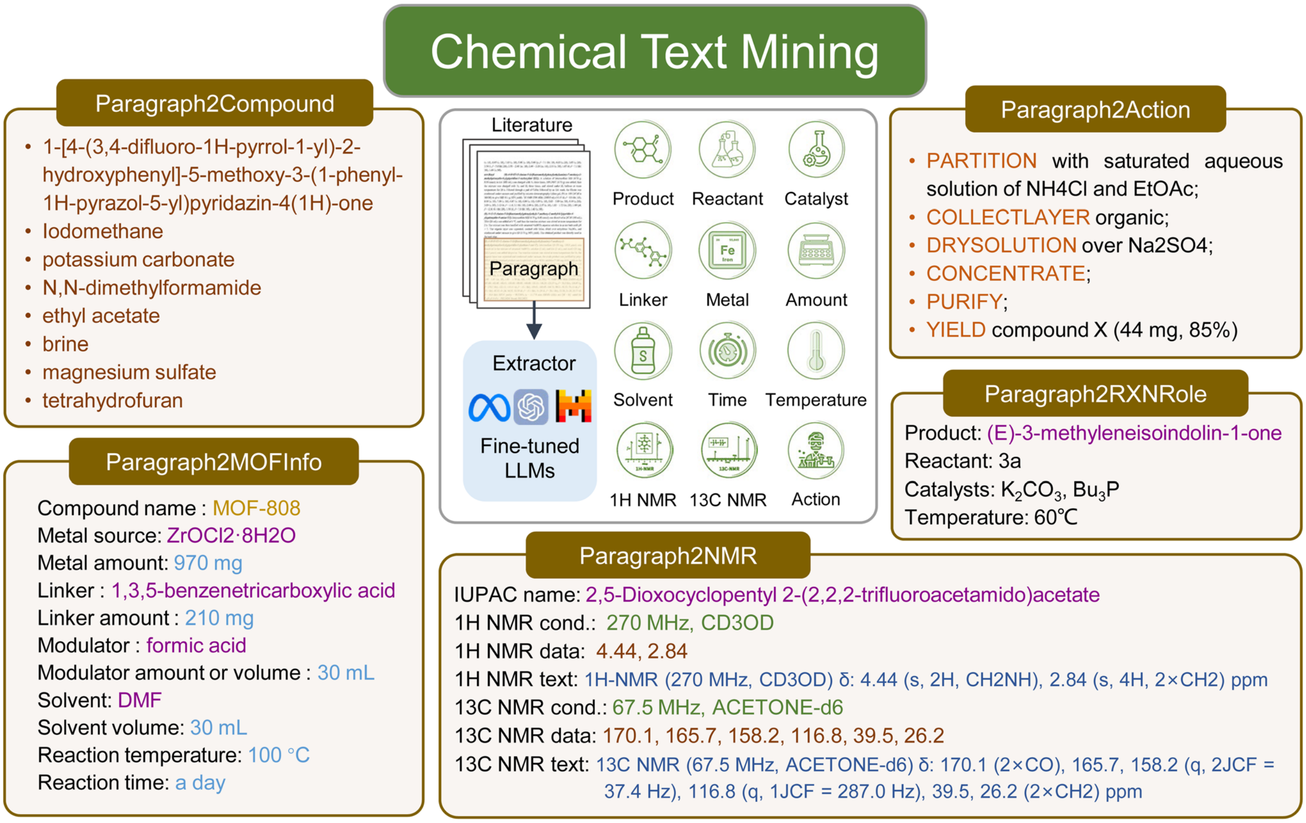

Chemical Text Mining
Paragraph2Compound
1-[4-(3,4-difluoro-1H-pyrrol-1-yl)-2-hydroxyphenyl]-5-methoxy-3-(1-phenyl-1H-pyrazol-5-yl)pyridazin-4(1H)-one
Iodomethane
potassium carbonate
N,N-dimethylformamide
ethyl acetate
brine
magnesium sulfate
tetrahydrofuran
Literature
Paragraph
Extractor
Fine-tuned LLMs
Product
Reactant
Catalyst
Linker
Metal
Amount
Solvent
Time
Temperature
1H NMR
13C NMR
Action
Paragraph2Action
PARTITION with saturated aqueous solution of NH4Cl and EtOAc;
COLLECTLAYER organic;
DRYSOLUTION over Na2SO4;
CONCENTRATE;
PURIFY;
YIELD compound X (44 mg, 85%)
Paragraph2RXNRole
Product: (E)-3-methyleneisoindolin-1-one
Reactant: 3a
Catalysts: K2CO3, Bu3P
Temperature: 60°C
Paragraph2MOFInfo
Compound name : MOF-808
Metal source: ZrOCl2·8H2O
Metal amount: 970 mg
Linker : 1,3,5-benzenetricarboxylic acid
Linker amount : 210 mg
Modulator : formic acid
Modulator amount or volume : 30 mL
Solvent: DMF
Solvent volume: 30 mL
Reaction temperature: 100 °C
Reaction time: a day
Paragraph2NMR
IUPAC name: 2,5-Dioxocyclopentyl 2-(2,2,2-trifluoroacetamido)acetate
1H NMR cond.: 270 MHz, CD3OD
1H NMR data: 4.44, 2.84
1H NMR text: 1H-NMR (270 MHz, CD3OD) δ: 4.44 (s, 2H, CH2NH), 2.84 (s, 4H, 2×CH2) ppm
13C NMR cond.: 67.5 MHz, ACETONE-d6
13C NMR data: 170.1, 165.7, 158.2, 116.8, 39.5, 26.2
13C NMR text: 13C NMR (67.5 MHz, ACETONE-d6) δ: 170.1 (2×CO), 165.7, 158.2 (q, 2JCF = 37.4 Hz), 116.8 (q, 1JCF = 287.0 Hz), 39.5, 26.2 (2×CH2) ppm

Fig. 1 Schematics of cheminformatics insights to be extracted from paragraphs. And illustration of the five practical tasks in chemical text mining with the respective example outputs, including Paragraph2Compound, Paragraph2RXNRole, Paragraph2MOFInfo, Paragraph2NMR, and Paragraph2Action.

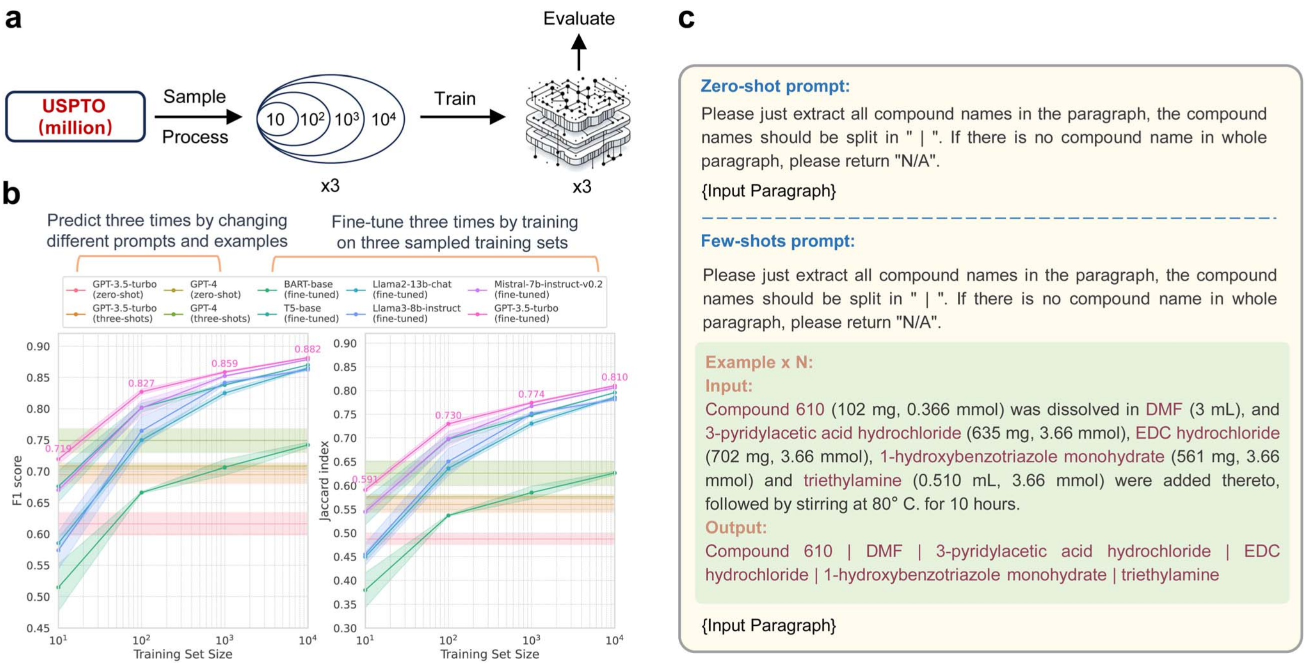
extraction, and conversion reaction paragraphs into action sequences. We found that fine-tuning GPT models significantly enhances performance in text mining tasks, compared to prompt-only versions, while also reducing dependency on the repetitive and extensive prompt engineering experiments. Meanwhile, we also evaluated prevalent generative pre-trained language models, such as Mistral,[17] Llama3,[18] Llama2,[19] T5,[20] and BART.[21] Among these, fine-tuned ChatGPT (GPT-3.5-turbo) models achieved state-of-the-art (SOTA) performance across all five tasks. Remarkably, it even outperformed models that have been trained specifically for each task and subsequently fine-tuned, based on a significantly larger amount of in-domain data. This study highlights the potential of fine-tuning LLMs to revolutionize complex knowledge extraction with their versatility, robustness, and low code capability. Fine-tuned LLMs can be easily generalizable and can optimize the labor-intensive and time-consuming data collection workflow, even with few data. This will accelerate the discovery and creation of novel substances, making them powerful tools for universal use.

Results and discussion

Overview of chemical text mining tasks

Given the complex and diverse information embedded in chemical literature, we designed five extraction tasks to demonstrate the potential and practicality of LLMs in chemical text mining (Fig. 1). The Paragraph2Compound task is a relatively simple task, aiming to extract all chemical compound entities from the given paragraph. The Paragraph2RXNRole task is to label the reaction roles including the product, reactant, catalyst, temperature, solvent, time, and yield in the paragraph. The Paragraph2MOFInfo task is to extract all MOF synthesis information including the compound name, metal source, metal amount, linker, linker amount, modulator, modulator amount or volume, solvent, solvent volume, reaction temperature and reaction time. The Paragraph2NMR task is designed to extract the IUPAC name, experimental conditions including frequency and solvent as well as chemical shift data for both ^{1}H NMR and ^{13}C NMR spectra. The Paragraph2Action task is to convert experimental procedures to structured synthetic steps (action sequences). The details of datasets used for the five chemical text mining tasks are listed in Table S1.† All tasks are unified to sequence-to-sequence formats to facilitate the use of LLMs. The details about using LLMs with prompt-engineering and fine-tuning can be found in the Methods section.

Paragraph2Compound—extract all chemical entities. Fig. 2a illustrates the process of random sampling from millions of paragraph–entity pairs, which refer to UPSTO annotations. It starts by randomly selecting 10 000 samples, followed by randomly picking 1000, then 100, and finally 10. This sampling process ensures that each smaller subset is included in the larger one, with each subset used for individual training. Fig. 2b demonstrates the performance of prompt-only models and fine-tuned models, which are evaluated on a consistent evaluation set of 1000 samples across varying training data sizes. These results are obtained from three independent trials. In the case of prompt-only models, randomness is intentionally introduced by altering the prompt and examples (Fig. 2c and S2†). Given the



Zero-shot prompt:

Please just extract all compound names in the paragraph, the compound names should be split in " | ". If there is no compound name in whole paragraph, please return "N/A".

{Input Paragraph}

Few-shots prompt:

Please just extract all compound names in the paragraph, the compound names should be split in " | ". If there is no compound name in whole paragraph, please return "N/A".

Example x N:

Input:

Compound 610 (102 mg, 0.366 mmol) was dissolved in DMF (3 mL), and 3-pyridylacetic acid hydrochloride (635 mg, 3.66 mmol), EDC hydrochloride (702 mg, 3.66 mmol), 1-hydroxybenzotriazole monohydrate (561 mg, 3.66 mmol) and triethylamine (0.510 mL, 3.66 mmol) were added thereto, followed by stirring at 80° C. for 10 hours.

Output:

Compound 610 | DMF | 3-pyridylacetic acid hydrochloride | EDC hydrochloride | 1-hydroxybenzotriazole monohydrate | triethylamine

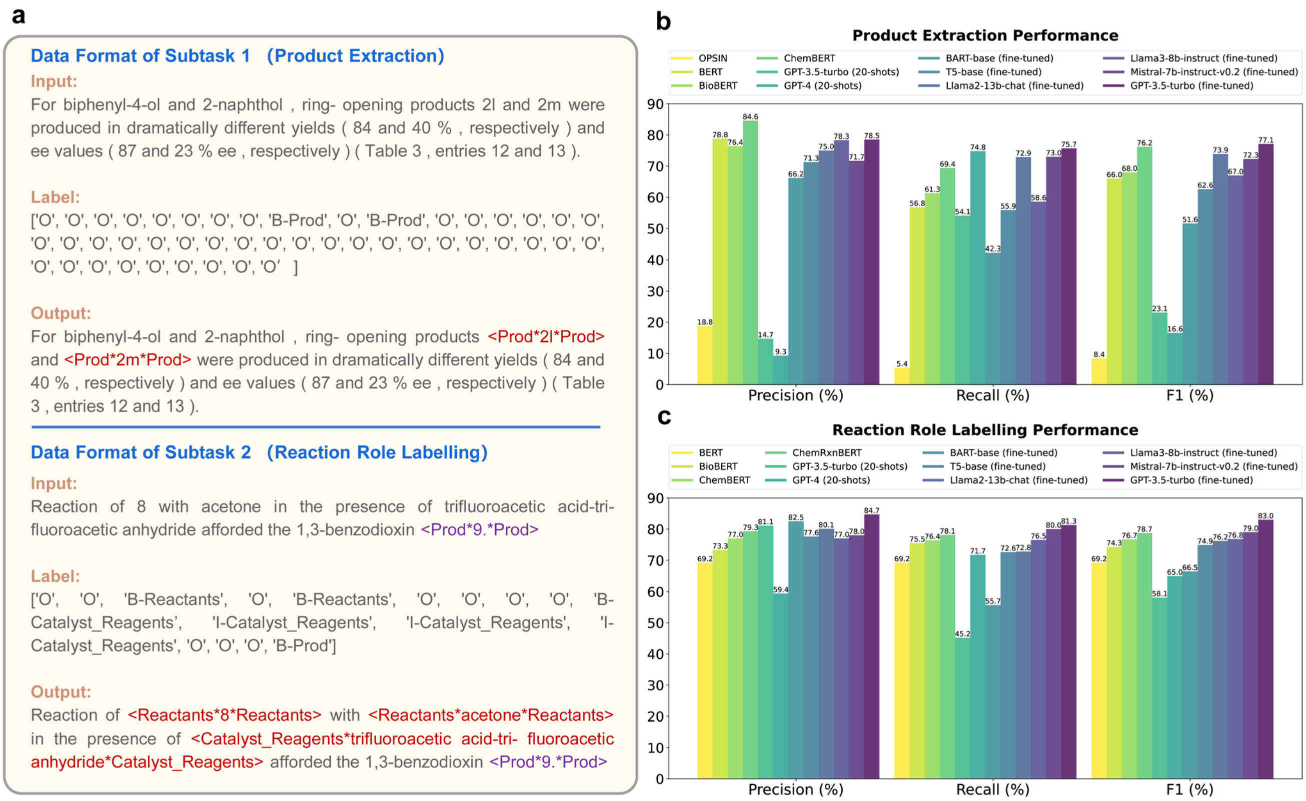
{Input Paragraph}

Fig. 2 (a) The workflow of sampling and training based on the USPTO dataset for the Paragraph2Compound task. (b) The performance of different models across varying sizes of the training set. The data point and the shaded areas represent, respectively, the mean values and standard deviations derived from three independent trials. (c) Example of the zero-shot and few-shot prompts utilized.

task's straightforward nature and clear instructions, even the prompt-only language models achieved decent F1 scores over 0.6. For fine-tuned models, the sampling and training process for the training set is repeated three times, as depicted in Fig. 2a. As shown in Fig. 2b, all fine-tuned models demonstrate a performance improvement, especially in terms of the F1 score and Jaccard index, proportional to the increase in dataset size. These models outperform the prompt-only models designed for this task. When the training data size is substantial enough, the F1 scores of the fine-tuned models can reach close to 90%, and the Jaccard index can approach 80%. Notably, fine-tuned LLMs such as GPT-3.5-turbo showed minimal fluctuations and superior performance. However, it is essential to emphasize that the cost of fine-tuning GPT-3.5-turbo increased tenfold with each tenfold increase in data volume. Our experimentation was capped at 10 000 training samples for 3 epochs due to OpenAI's limitations, resulting in a nearly 90-dollar expense to fine-tune GPT-3.5-turbo—a low cost-effective investment in computational resources. In contrast, other fine-tuned language models have displayed notable cost advantages in this relatively simple compound name entity recognition task.

Paragraph2RXNRole—extract the product and label the reaction role. According to Guo *et al.*,[8] the Paragraph2RXNRole task comprises two subtasks. The first is to extract the central product, and the second is to label the associated reaction roles within specified paragraphs (Fig. 3a). For the two tasks, Guo *et al.* developed two-stage BERT-like token-multi-classification models. To enable a fair comparison with generative language models, we converted the data into sequence-to-sequence formats by adding <Role*Compound*Role> annotations to the input paragraphs. We then converted the language models' outputs back into lists of BIO-tags, followed by post-processing to align with the original BIO-tag labels for assessment. Notably, even when utilizing prompt engineering with 20-shot examples (Fig. S3 and S4†), GPT-3.5 and GPT-4 perform poorly on two Paragraph2RXNRole tasks, which may result from the complicated syntax cases and limited context length (Fig. 3b and c). However, the fine-tuned GPT models perform well.

For product extraction, the fine-tuned GPT-3.5-turbo (best over one epoch) achieved an F1 score of 77.1%, slightly surpassing the previous SOTA approach, ChemBERT, which scored 76.2% (Fig. 3b). For reaction role labelling, the fine-tuned GPT-3.5-turbo (best over five epochs) achieved an F1 score of 83.0%, significantly outperforming the previous SOTA approach, ChemRxnBERT, which scored 78.7% (Fig. 3c). It's notable that the fine-tuned GPT-3.5-turbo models, which cost only $1 and $5 respectively, demonstrated extremely high cost-effectiveness with small training datasets. In contrast, ChemBERT was domain-adaptive pre-trained on 9 478 043 sentences from 200 000 journal articles, and ChemRxnBERT was further task-adaptive trained on 944 733 reaction-inclusive sentences. We should also mention that the outputs of fine-tuned GPTs, Mistrals and Llamas align almost perfectly with the input text, with over 99% post-processing-free ratios. On the other hand,



Data Format of Subtask 1 (Product Extraction)

Input:

For biphenyl-4-ol and 2-naphthol , ring- opening products 2l and 2m were produced in dramatically different yields (84 and 40 % , respectively) and ee values (87 and 23 % ee , respectively) (Table 3 , entries 12 and 13).

Label:

['O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-Prod', 'O', 'B-Prod', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O']

Output:

For biphenyl-4-ol and 2-naphthol , ring- opening products <Prod*2l*Prod> and <Prod*2m*Prod> were produced in dramatically different yields (84 and 40 % , respectively) and ee values (87 and 23 % ee , respectively) (Table 3 , entries 12 and 13).

Data Format of Subtask 2 (Reaction Role Labelling)

Input:

Reaction of 8 with acetone in the presence of trifluoroacetic acid-tri-fluoroacetic anhydride afforded the 1,3-benzodioxin <Prod*9.*Prod>

Label:

['O', 'O', 'B-Reactants', 'O', 'B-Reactants', 'O', 'O', 'O', 'O', 'B-Catalyst_Reagents', 'I-Catalyst_Reagents', 'I-Catalyst_Reagents', 'I-Catalyst_Reagents', 'O', 'O', 'O', 'B-Prod']

Output:

Reaction of <Reactants*8*Reactants> with <Reactants*acetone*Reactants> in the presence of <Catalyst_Reagents*trifluoroacetic acid-tri- fluoroacetic anhydride*Catalyst_Reagents> afforded the 1,3-benzodioxin <Prod*9.*Prod>

Fig. 3 (a) Data formats of two subtasks in the Paragraph2RXNRole task. (b) Performance of product extraction. Concrete values can be found in Table S7.† (c) Performance of reaction role labelling. Concrete values can be found in Table S8.†

most outputs of fine-tuned T5 and BART require additional alignment due to their tokenization and vocabulary limitations, with a ratio of only 31% that does not require post-processing. Even after post-processing, the F1 scores of T5 and BART were significantly lower than those of token-classification BERT-like models or large language models.

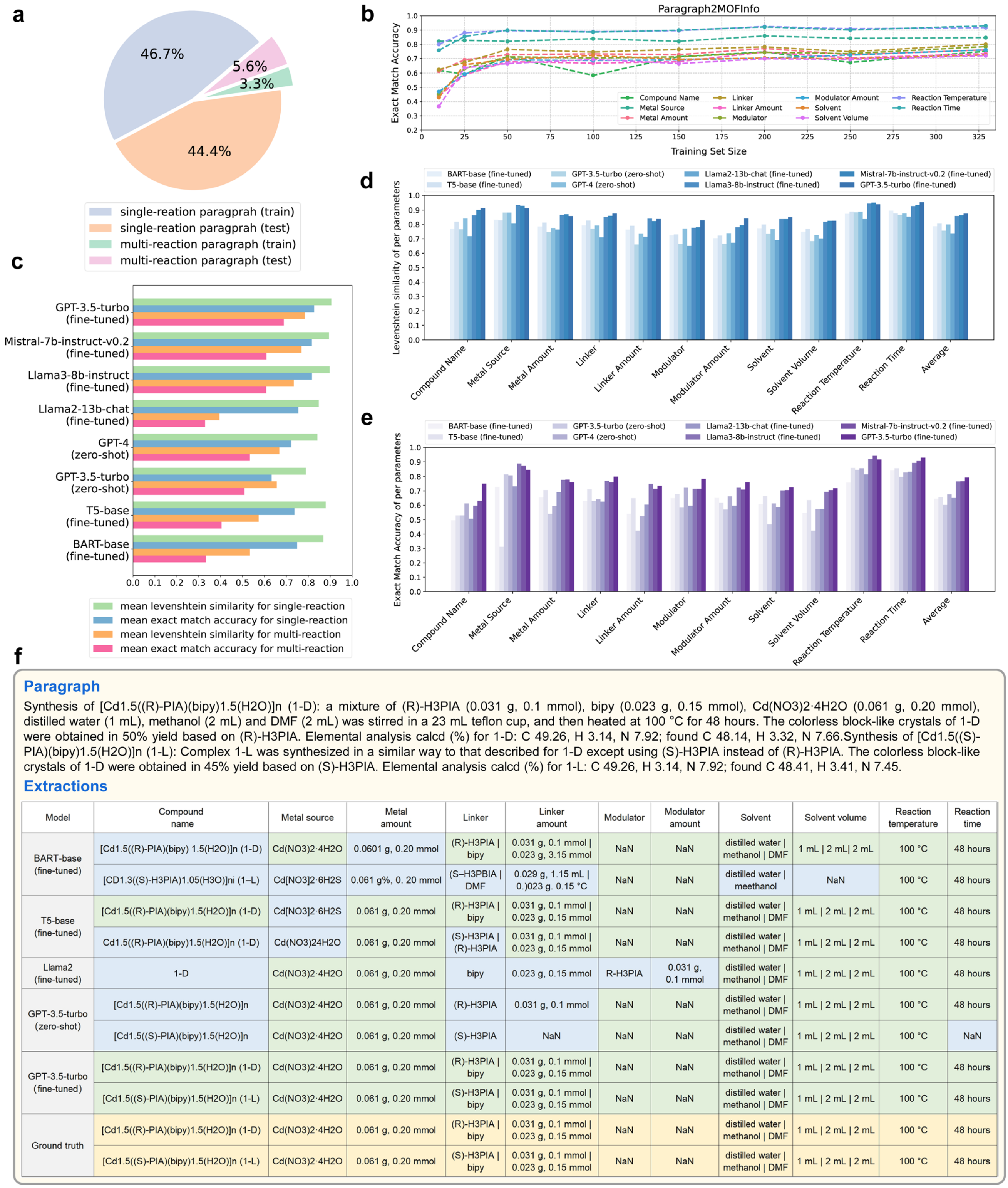
Paragraph2MOFInfo—extraction of MOF synthesis information. Our re-annotated dataset for the Paragraph2MOFInfo task displayed in Fig. 4a mostly contains single reaction paragraphs with a few featuring multiple reactions. We used Levenshtein similarity and exact accuracy as metrics to objectively assess the models' ability to extract formatted data that fully comply with the customized requirements in the task. This approach is more objective and accurate with less manual intervention, compared to the manual analysis and evaluation used by Zheng *et al.*[14] The dataset is divided into a training set and a test set, each containing 329 samples. We evaluated the performance of fine-tuned GPT-3.5-turbo by varying the size of training data from 10 to 329, and observed convergence on the testing set, suggesting saturation in the amount of training data (Fig. 4b). The fine-tuned GPT-3.5-turbo significantly outperforms the GPT-3.5-turbo with prompt engineering, improving exact match accuracy by over 20% for both single and multiple reactions (Fig. 4c, and S5†). It also surpasses other fine-tuned models, especially when handling complex multi-reaction paragraphs.

Exact accuracy rates for single and multiple reactions are 82.7% and 68.8%, respectively (Fig. 4c). As depicted in Fig. 4d and e, while most models achieve high Levenshtein similarity across the 11 parameters, only a few maintain high exact accuracy, which is the golden metric that we mainly focus on.

Considering that some MOF synthesis paragraphs may include multiple reactions, we provide an example of multi-reaction extraction by various models in Fig. 4f. The paragraph includes two reactions, the first with (R)-H3PIA and bipy as linkers, providing all reaction conditions explicitly, and the second with the substitution of (R)-H3PIA with (S)-H3PIA, keeping all other conditions unchanged. Most models successfully interpreted the semantics and extracted two reactions from the MOF synthesis paragraph. However, only the fine-tuned ChatGPT perfectly extracted information that matched our annotated ground truth. Other models showed varying degrees of incompleteness, particularly with items involving multiple components and their quantities.

Paragraph2NMR—extract NMR chemical shifts and conditions. The impact of training set sizes and the use of prompt engineering on the performance of fine-tuning GPT-3.5-turbo in extracting NMR information is illustrated in Fig. 5a. Regardless of the training data size for fine-tuning (ranging from 25 to 300), or the presence of prompt engineering, there are hardly any significant fluctuations in performance. This holds true for metrics such as Levenshtein similarity and exact match accuracy of the fine-tuned GPT-3.5-turbo when the numbers of training samples exceed 50. This demonstrates the strong learning capability and robustness of LLMs. Fig. 5b illustrates the performance of different generative language models using the same 200 training data. In terms of Levenshtein similarity, a metric based on the edit distance, almost all fine-tuned language models achieved impressive scores, outperforming GPT models that solely rely on prompt engineering (Fig. 5b and S6†). However, when considering the exact match accuracy metric, where each character must perfectly align with the ground truth count, LLMs such as GPTs, Mistral, and Llama3 take the lead. Though fine-tuned T5 and BART manage to extract the majority of the text, they often miss or mistakenly copy several characters. This contributes to a significant decrease in their exact match accuracy metric, as shown in Fig. 5c. In this context, the extraction of long complex text by LLMs is more standardized and high-quality, aligning more closely with human expectations. It is worth noting that using carefully designed prompts has almost no impact on the results, which proves that the fine-tuned LLMs are prompt independent. Most importantly, fine-tuning open-source LLMs such as Mistral-7b-instruct-v-0.2 and Llama3-8b-instruct provides an alternative approach for deploying text mining locally, given its exceptionally high exact match accuracy.

Paragraph2Action—action sequence extracted from an experimental procedure. The above-mentioned extraction tasks simply require the model to replicate specific information from the paragraph. However, the Paragraph2Action task requires the model to understand and transform the paragraph and convert experimental procedures to structured synthetic steps (action sequences). Clearly, GPT models with prompt engineering have difficulty with this task, especially when it involves multiple complex conversions and insufficient prompt descriptions (Table 1, Fig. S7†). To gauge the maximum potential of GPT models using only prompts, we incrementally increased the number of transformation examples from 6 to 60. Despite encompassing all types of actions at least once and nearly reaching the token limit of 4096 for GPT-3.5-turbo and 8192 for GPT-4, their performance in the few-shot scenario remains disappointingly poor. The currently best-performing LLM GPT-4 with 60 examples for in-context learning achieved only 32.7% full sentence exact accuracy, a BLEU score of 65.0, and a Levenshtein similarity of 72.8. However, fine-tuning pre-trained language models with a small amount of data could yield decent results (Table 1). Remarkably, fine-tuning LLMs such as Mistral-7b-instruct-v0.2 and GPT-3.5-turbo on 1060 hand annotated training data, we achieved 64.8% and 63.6% full sentence exact accuracy. The fine-tuning process took only 8 minutes (2 epochs) for Mistral on 4 × A100 and 1 hour (4 epochs) for GPT-3.5-turbo. These metrics surpass the SOTA results previously reported by Vaucher *et al.*,[1] which used an ensemble of three models, each task-adaptively pre-trained on 2 million rule-based data and refined on 14 168 augmented data. Interestingly, further improvement was achieved by augmenting the training data size to 14 168 when fine-tuning GPT-3.5-turbo. This resulted in 69.0% full sentence exact accuracy, an 86.4 modified BLEU score, and an 89.9% Levenshtein similarity (Table 1). For autonomous robots, it is challenging to generate instructions that follow strict syntax rules. Fine-tuning LLMs plays a crucial role in bridging the gap between fuzzy natural language and structured machine-executable programming languages, significantly improving the accuracy of



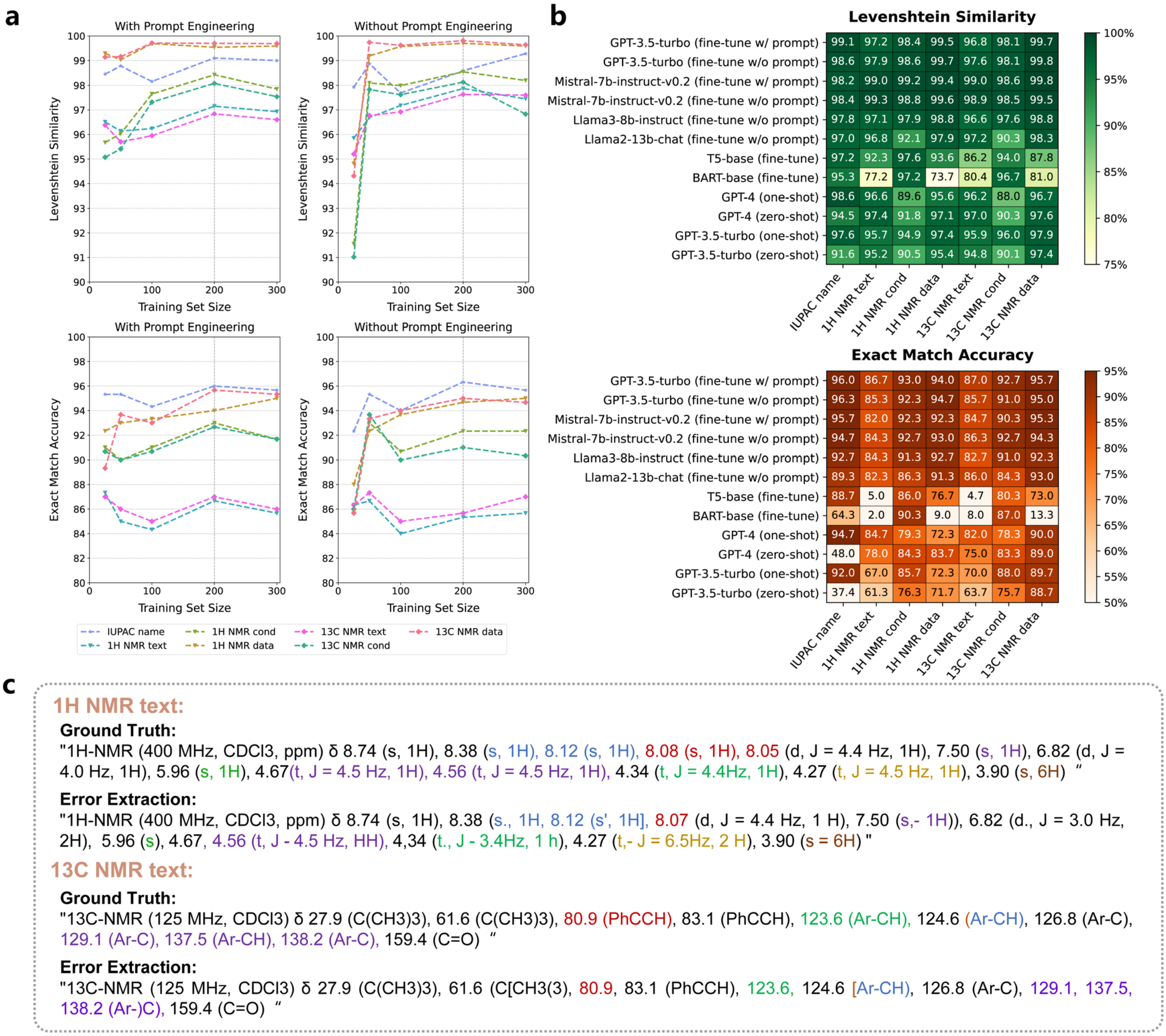
Paragraph

Synthesis of [Cd1.5((R)-PIA)(bipy)1.5(H2O)]n (1-D): a mixture of (R)-H3PIA (0.031 g, 0.1 mmol), bipy (0.023 g, 0.15 mmol), Cd(NO3)2·4H2O (0.061 g, 0.20 mmol), distilled water (1 mL), methanol (2 mL) and DMF (2 mL) was stirred in a 23 mL teflon cup, and then heated at 100 °C for 48 hours. The colorless block-like crystals of 1-D were obtained in 50% yield based on (R)-H3PIA. Elemental analysis calcd (%) for 1-D: C 49.26, H 3.14, N 7.92; found C 48.14, H 3.32, N 7.66.Synthesis of [Cd1.5((S)-PIA)(bipy)1.5(H2O)]n (1-L): Complex 1-L was synthesized in a similar way to that described for 1-D except using (S)-H3PIA instead of (R)-H3PIA. The colorless block-like crystals of 1-D were obtained in 45% yield based on (S)-H3PIA. Elemental analysis calcd (%) for 1-L: C 49.26, H 3.14, N 7.92; found C 48.41, H 3.41, N 7.45.

Extractions

Model	Compound name	Metal source	Metal amount	Linker	Linker amount	Modulator	Modulator amount	Solvent	Solvent volume	Reaction temperature	Reaction time
BART-base (fine-tuned)	[Cd1.5((R)-PIA)(bipy) 1.5(H2O)]n (1-D)	Cd(NO3)2·4H2O	0.0601 g, 0.20 mmol	(R)-H3PIA | bipy	0.031 g, 0.1 mmol | 0.023 g, 3.15 mmol	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL| 2 mL	100 °C	48 hours
	[CD1.3((S)-H3PIA)1.05(H3O)]ni (1–L)	Cd[NO3]2·6H2S	0.061 g%, 0. 20 mmol	(S–H3PBIA | DMF	0.029 g, 1.15 mL | 0.)023 g. 0.15 °C	NaN	NaN	distilled water | meethanol	NaN	100 °C	48 hours
T5-base (fine-tuned)	[Cd1.5((R)-PIA)(bipy)1.5(H2O)]n (1-D)	Cd[NO3]2·6H2S	0.061 g, 0.20 mmol	(R)-H3PIA | bipy	0.031 g, 0.1 mmol | 0.023 g, 0.15 mmol	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	48 hours
	Cd1.5((R)-PIA)(bipy)1.5(H2O)]n (1-D)	Cd(NO3)24H2O	0.061 g, 0.20 mmol	(S)-H3PIA | (R)-H3PIA	0.031 g, 0.1 mmol | 0.023 g, 0.15 mmol	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	48 hours
Llama2 (fine-tuned)	1-D	Cd(NO3)2·4H2O	0.061 g, 0.20 mmol	bipy	0.023 g, 0.15 mmol	R-H3PIA	0.031 g, 0.1 mmol	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	48 hours
GPT-3.5-turbo (zero-shot)	[Cd1.5((R)-PIA)(bipy)1.5(H2O)]n	Cd(NO3)2·4H2O	0.061 g, 0.20 mmol	(R)-H3PIA	0.031 g, 0.1 mmol	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	48 hours
	[Cd1.5((S)-PIA)(bipy)1.5(H2O)]n	Cd(NO3)2·4H2O	0.061 g, 0.20 mmol	(S)-H3PIA	NaN	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	NaN
GPT-3.5-turbo (fine-tuned)	[Cd1.5((R)-PIA)(bipy)1.5(H2O)]n (1-D)	Cd(NO3)2·4H2O	0.061 g, 0.20 mmol	(R)-H3PIA | bipy	0.031 g, 0.1 mmol | 0.023 g, 0.15 mmol	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	48 hours
	[Cd1.5((S)-PIA)(bipy)1.5(H2O)]n (1-L)	Cd(NO3)2·4H2O	0.061 g, 0.20 mmol	(S)-H3PIA | bipy	0.031 g, 0.1 mmol | 0.023 g, 0.15 mmol	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	48 hours
Ground truth	[Cd1.5((R)-PIA)(bipy)1.5(H2O)]n (1-D)	Cd(NO3)2·4H2O	0.061 g, 0.20 mmol	(R)-H3PIA | bipy	0.031 g, 0.1 mmol | 0.023 g, 0.15 mmol	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	48 hours
	[Cd1.5((S)-PIA)(bipy)1.5(H2O)]n (1-L)	Cd(NO3)2·4H2O	0.061 g, 0.20 mmol	(S)-H3PIA | bipy	0.031 g, 0.1 mmol | 0.023 g, 0.15 mmol	NaN	NaN	distilled water | methanol | DMF	1 mL | 2 mL | 2 mL	100 °C	48 hours

Fig. 4 (a) A statistic of the Paragraph2MOFInfo dataset. (b) The performance of fine-tuned GPT-3.5-turbo across varying sizes of the training set. (c) Mean performance of Levenshtein similarity and exact match accuracy for extracting paragraphs containing single reactions and multiple reactions, respectively, by different models. Concrete values can be found in Table S9.† (d) Levenshtein similarity for 11 parameters in the Paragraph2MOFInfo task. Concrete values can be found in Table S10.† (e) Exact match accuracy for 11 parameters in the Paragraph2MOFInfo task. Concrete values can be found in Table S11.† (f) An example of extractions by different models from a multi-reaction MOF synthesis paragraph. The cells in yellow represented the ground truth. The cells in green represented the exact match predictions. The cells in blue represented the incorrect predictions.



Levenshtein Similarity

	IUPAC name	1H NMR text	1H NMR cond	1H NMR data	13C NMR text	13C NMR cond	13C NMR data
GPT-3.5-turbo (fine-tune w/ prompt)	99.1	97.2	98.4	99.5	96.8	98.1	99.7
GPT-3.5-turbo (fine-tune w/o prompt)	98.6	97.9	98.6	99.7	97.6	98.1	99.8
Mistral-7b-instruct-v0.2 (fine-tune w/ prompt)	98.2	99.0	99.2	99.4	99.0	98.6	99.8
Mistral-7b-instruct-v0.2 (fine-tune w/o prompt)	98.4	99.3	98.8	99.6	98.9	98.5	99.5
Llama3-8b-instruct (fine-tune w/o prompt)	97.8	97.1	97.9	98.8	96.6	97.6	98.8
Llama2-13b-chat (fine-tune w/o prompt)	97.0	96.8	92.1	97.9	97.2	90.3	98.3
T5-base (fine-tune)	97.2	92.3	97.6	93.6	86.2	94.0	87.8
BART-base (fine-tune)	95.3	77.2	97.2	73.7	80.4	96.7	81.0
GPT-4 (one-shot)	98.6	96.6	89.6	95.6	96.2	88.0	96.7
GPT-4 (zero-shot)	94.5	97.4	91.8	97.1	97.0	90.3	97.6
GPT-3.5-turbo (one-shot)	97.6	95.7	94.9	97.4	95.9	96.0	97.9
GPT-3.5-turbo (zero-shot)	91.6	95.2	90.5	95.4	94.8	90.1	97.4

Exact Match Accuracy

	IUPAC name	1H NMR text	1H NMR cond	1H NMR data	13C NMR text	13C NMR cond	13C NMR data
GPT-3.5-turbo (fine-tune w/ prompt)	96.0	86.7	93.0	94.0	87.0	92.7	95.7
GPT-3.5-turbo (fine-tune w/o prompt)	96.3	85.3	92.3	94.7	85.7	91.0	95.0
Mistral-7b-instruct-v0.2 (fine-tune w/ prompt)	95.7	82.0	92.3	92.3	84.7	90.3	95.3
Mistral-7b-instruct-v0.2 (fine-tune w/o prompt)	94.7	84.3	92.7	93.0	86.3	92.7	94.3
Llama3-8b-instruct (fine-tune w/o prompt)	92.7	84.3	91.3	92.7	82.7	91.0	92.3
Llama2-13b-chat (fine-tune w/o prompt)	89.3	82.3	86.3	91.3	86.0	84.3	93.0
T5-base (fine-tune)	88.7	5.0	86.0	76.7	4.7	80.3	73.0
BART-base (fine-tune)	64.3	2.0	90.3	9.0	8.0	87.0	13.3
GPT-4 (one-shot)	94.7	84.7	79.3	72.3	82.0	78.3	90.0
GPT-4 (zero-shot)	48.0	78.0	84.3	83.7	75.0	83.3	89.0
GPT-3.5-turbo (one-shot)	92.0	67.0	85.7	72.3	70.0	88.0	89.7
GPT-3.5-turbo (zero-shot)	37.4	61.3	76.3	71.7	63.7	75.7	88.7

1H NMR text:

Ground Truth:
"1H-NMR (400 MHz, CDCl3, ppm) δ 8.74 (s, 1H), 8.38 (s, 1H), 8.12 (s, 1H), 8.08 (s, 1H), 8.05 (d, J = 4.4 Hz, 1H), 7.50 (s, 1H), 6.82 (d, J = 4.0 Hz, 1H), 5.96 (s, 1H), 4.67(t, J = 4.5 Hz, 1H), 4.56 (t, J = 4.5 Hz, 1H), 4.34 (t, J = 4.4Hz, 1H), 4.27 (t, J = 4.5 Hz, 1H), 3.90 (s, 6H) "

Error Extraction:
"1H-NMR (400 MHz, CDCl3, ppm) δ 8.74 (s, 1H), 8.38 (s., 1H, 8.12 (s', 1H], 8.07 (d, J = 4.4 Hz, 1 H), 7.50 (s,- 1H)), 6.82 (d., J = 3.0 Hz, 2H), 5.96 (s), 4.67, 4.56 (t, J - 4.5 Hz, HH), 4,34 (t., J - 3.4Hz, 1 h), 4.27 (t,- J = 6.5Hz, 2 H), 3.90 (s = 6H) "

13C NMR text:

Ground Truth:
"13C-NMR (125 MHz, CDCl3) δ 27.9 (C(CH3)3), 61.6 (C(CH3)3), 80.9 (PhCCH), 83.1 (PhCCH), 123.6 (Ar-CH), 124.6 (Ar-CH), 126.8 (Ar-C), 129.1 (Ar-C), 137.5 (Ar-CH), 138.2 (Ar-C), 159.4 (C=O) "

Error Extraction:
"13C-NMR (125 MHz, CDCl3) δ 27.9 (C(CH3)3), 61.6 (C[CH3(3), 80.9, 83.1 (PhCCH), 123.6, 124.6 [Ar-CH), 126.8 (Ar-C), 129.1, 137.5, 138.2 (Ar-)C), 159.4 (C=O) "

Fig. 5 (a) The performance of fine-tuned GPT-3.5-turbo with and without prompt engineering as it varies with training data size in the Pargraph2NMR task. (b) Heat map illustrating Levenshtein similarity and exact match accuracy of various models in extracting NMR information. Concrete values can be found in Tables S12 and S13.† (c) Examples of error extractions by T5 and BART, compared with the ground truth.

customization with a small amount of annotated data. In similar tasks involving "fuzzy rules" or hard-to-define extraction, fine-tuning LLMs might offer considerable advantages in tailoring the transformation.

Comparison of different methods for chemical text mining

Chemical text mining expedites scientific discovery in chemistry. Previously, tasks involving complex chemical language and sophisticated processing depended on rule-based matching algorithms and custom-built domain-specific models. Now, leveraging universal LLMs' semantic understanding, long context window, and generation abilities offers promising and general approaches. These methods are illustrated in Fig. 6. In prompt engineering scenarios, LLMs' parameters remain fixed, solely relying on the provided examples to extract from new paragraphs. As for the training and fine-tuning process, a model learns the statistic extraction patterns from the training data by adjusting and optimizing the internal parameters.

Undoubtedly, leveraging LLMs with prompt engineering is the most attractive approach because it does not require writing any code or retraining model parameters, only interacting with the large model through natural language instructions. However, relying solely on instructions without any examples (zero-shot) also makes it difficult to standardize the output of LLMs, which is crucial for formatting data extraction tasks. In the case of extracting NMR based solely on instructions (Fig. S8†), we repeatedly modify the instructions to ensure that the model can generate expected formatting results on a certain paragraph. However, when we used this carefully designed prompt for other paragraphs containing NMR, the extraction

Table 1 Performance on the Paragraph2Action task[a]

Model	Strategy	100% acc.	90% acc.	75% acc.	Modified BLEU score	Levenshtein similarity	Cost
GPT-3.5-turbo (6-shot)	Prompt engineering without fine-tuning	8.2	16.8	34.7	38.6	59.4	905 mean tokens
GPT-3.5-turbo (12-shot)		8.8	19.3	42.3	43.1	62.3	1374 mean tokens
GPT-3.5-turbo (18-shot)		13.1	23.3	42.6	44.4	64.3	1670 mean tokens
GPT-3.5-turbo (24-shot)		14.8	25.9	45.5	47.0	65.8	2598 mean tokens
GPT-3.5-turbo (30-shot)		13.9	26.4	47.2	49.5	66.0	3610 mean tokens
GPT-4 (6-shot)	Prompt engineering without fine-tuning	13.4	23.3	44.9	44.7	54.5	861 mean tokens
GPT-4 (12-shot)		20.7	30.7	51.1	51.4	69.2	1357 mean tokens
GPT-4 (18-shot)		21.9	33.0	56.5	53.8	63.0	1631 mean tokens
GPT-4 (24-shot)		22.7	35.8	58.2	56.7	65.1	2546 mean tokens
GPT-4 (30-shot)		26.1	40.0	61.6	59.8	67.7	3611 mean tokens
GPT-4 (60-shot)		32.7	43.8	63.3	65.0	72.8	7010 mean tokens, $ 41
Transformer (single model)*	No task-adaptive pretraining and fine-tuning on hand-annotated data (1060)	13.1	15.1	21.9	22.5	45.9	—
BART-base (fine-tuned)		51.1	65.9	77.6	73.2	83.9	6 min on 1 × 40 GB A100
T5-base (fine-tuned)		57.7	71.6	83.2	81.8	86.8	10 min on 1 × 40 GB A100
Lama2-13b-chat (qlora fine-tuned)		56.8	66.8	80.7	80.3	86.0	40 min on 1 × 40 GB A100
Lama3-8b-instruct (fine-tuned)		59.7	70.2	83.2	82.2	86.3	30 min on 4 × 40 GB A100
Mistral-7b-instruct-v0.2 (fine-tuned)		**64.8**	**73.6**	**85.5**	**85.9**	**88.7**	8 min on 4 × 40 GB A100
GPT-3.5-turbo (fine-tuned)		63.6	71.6	82.7	84.8	88.1	4 epochs, total 1 h, $ 4
Transformer (single model)*	No task-adaptive pretraining and fine-tuning on augmented data (14 168)	37.8	47.7	62.8	64.7	76.4	—
BART-base (fine-tuned)		52.0	68.5	80.1	74.4	84.8	30 min on 1 × 40 GB A100
T5-base (fine-tuned)		59.7	74.1	82.4	84.1	87.1	100 min on 1 × 40 GB A100
Llama2-13b-chat (qlora fine-tuned)		62.2	71.6	84.1	84.3	87.5	5 hours on 1 × 40 GB A100
Lama3-8b-instruct (fine-tuned)		56.0	67.0	80.4	81.4	84.8	100 min on 4 × 40 GB A100
Mistral-7b-instruct-v0.2 (fine-tuned)		64.2	73.3	86.4	84.3	87.2	30 min on 4 × 40 GB A100
GPT-3.5-turbo (fine-tuned)		**69.0**	**78.1**	**86.9**	**86.4**	**89.9**	5 epochs, total 1.5 h, $ 92
Transformer (single model)*	Task-adaptive pretraining (2 M) and fine-tuning on hand-annotate data (1060)	56.8	67.3	80.4	81.5	85.7	—
Transformer (single model)*	Task-adaptive pretraining (2 M) and fine-tuning on augmented data (14 168)	59.4	70.5	81.8	84.3	86.7	—
Transformer (ensemble)*		60.8	71.3	82.4	85.0	86.6	—

[a] The symbol "*" represented the results reported by Vaucher *et al.* The result in black bold is the best performance. The details of fine-tuning cost can be found in Table S3.

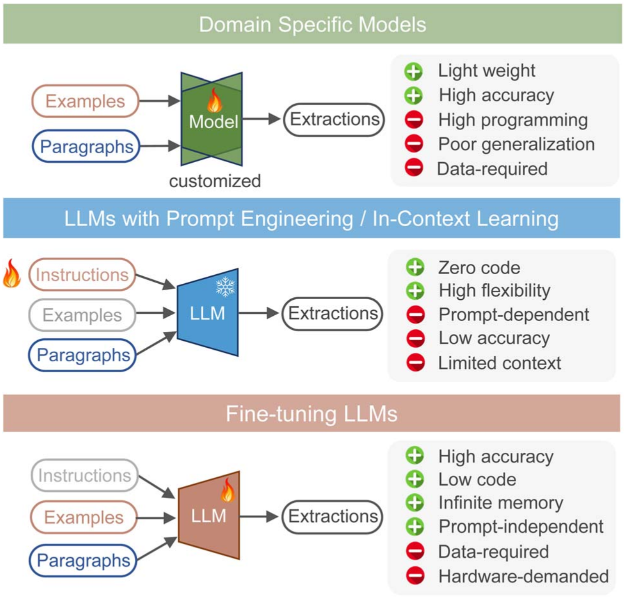


Fig. 6 Diagram of different approaches for text extraction.

results did not meet the qualified formatting requirements again. This zero-shot approach resulted in poor performance across all five tasks, even using GPT-4.

Apart from instructions, providing few example pairs of paragraph-extraction as context can help LLMs learn the extraction patterns. In these few-shot sceneries (Fig. 2c, S2–S7†), as shown in Table 1, increasing the number of examples leads LLMs to extract more structured outputs. Ideally, the whole training set should serve as context. However, the upper limit of in-context learning is constrained by the maximum input length due to the memory limitation. The versions of GPT-3.5-Turbo-0613 and GPT-4-0613 we tested were limited to 4096 and 8192 tokens, respectively. Hence, comparing prompt engineering methods in zero-shot and few-shot sceneries to fine-tuned models trained with complete datasets can be somewhat unfair.

To compare the performance of in-context learning and fine-tuning approaches objectively, we should use an equal number of examples for both context and the fine-tuning data set. Here, we tested the latest version of GPT-3.5-turbo-0125, which expands the context length to 16 K and supports fine-tuning. We used a variety of action sequences during sampling to cover as many action types as possible. As the number of examples increased from 30 to 60, 90 and 120, both the performances of in-context learning and fine-tuning are increasing (Table S14†). Even when the same number of examples was provided for in-context learning as fine-tuning, the fine-tuned model typically outperforms by 10–20% on metrics like exact match accuracy and modified BLEU score. This could be attributed to information loss in in-context learning, while fine-tuning adjusts parameters to learn extraction patterns, thus maintaining higher accuracy.

In the test, we also find two features of fine-tuning LLMs: rapid performance convergence with small amounts of data and efficient training generalization. For the four tasks utilizing manually annotated data, the LLM's performance rapidly improved and converged with increasing sample sizes (Fig. S11†). This highlights that hundreds of high-quality data are enough to train an effective extractor, which is typically a manageable workload for manual annotation. Besides, LLMs can be easily adapted for specific text extraction tasks, requiring only a few epochs and a low learning rate for fine-tuning (Table S3†). However, they are also prone to overfitting if trained for an excessive number of epochs.

Promising performance and potential of fine-tuning LLMs on chemical data mining. In this study, we have demonstrated the impressive efficacy, flexibility, and high exact accuracy of fine-tuning LLMs, regarding all kinds of text mining tasks as generative problems. An examination of incorrect predictions revealed that only a small proportion were entirely incorrect, while most were acceptable alternatives to the ground truth or even pointed out the incorrect labels (Fig. S12–S16†). These errors can be attributed to inconsistent annotation standards and the inherent ambiguity of terms with multiple interpretations or functions. Therefore, improving the formatted data extraction requires continuous efforts, including the refinement of specific rules and the enrichment of annotations prone to misinterpretation during training and inference. With detailed specifications and high-quality formatted data, the fine-tuning method based on LLMs is highly reliable.

Starting with five chemical extraction tasks, we have proved the effectiveness of fine-tuning LLMs in the relatively small testing sets. This approach, when utilized for large-scale extraction in the future, promises to greatly improve data collection efficiency and accelerate scientific research and experimentation. For the Paragraph2MOFInfo task, we can document the synthesis conditions along with other key information such as MOF structures, pore characteristics, and functional performance. Using these data, we can develop machine learning models to optimize the synthesis novel MOF materials with functions such as new catalysts, gas storage and separation. For the Paragraph2NMR task, we can collect extensive NMR data with the corresponding compound names from millions of synthesis literature documents. This can help create an NMR database for retrieving similar spectra and structures, as well as constructing predictive models to identify molecules structures and analysing complex mixtures, which support drug development and quality control. For the action sequence transformation task, the extracted information is beneficial for automatic and robotic synthesis. It will improve reproducibility and minimize human errors, especially in high-throughput experiments.

Apart from the five mentioned extraction tasks, it can be easily extended to tasks related to extracting information from scientific literature and transforming data into a simple user-friendly reaction format[22] that is both human- and machine-readable. This approach will significantly contribute to the development of extensive databases like the Open Reaction Database,[23,24] SciFinder[25] and Reaxys,[26] which gather comprehensive synthesis data through automated curation and expert verification, to make data more findable, accessible, interoperable, and reusable (FAIR).

Nevertheless, leveraging fine-tuned LLMs is still insufficient to extract all synthesis information from chemical literature, which contains extensive complex figure and form contents. Recently, some tools have been developed to recognize molecular images[27,28] and reaction diagrams[29,30] from the literature. Integrating LLMs with these image recognition tools or developing advanced large multimodal models (LMMs) may be a promising unified solution for further chemical data mining. Notably, when extracting large amounts of data from copyrighted literature, it's essential to access the necessary permissions from scientific publications.

Herein, we have scratched the surface of the vast potential of LLMs in chemistry and materials science by fine-tuning LLMs for chemical text mining. We may notice that the gap between open-source language models and proprietary GPTs (GPT-3.5-turbo and GPT-4) has been narrowing from Llama2 to Llama3 and Mistral. This progress is due to the concerted efforts of researchers and communities in the direction of LLMs. Technically, advancements like more effective fine-tuning strategies, improved open-source model architectures, faster inference approaches, wider context windows, higher quality corpus, and lower computational costs in the era of LLMs are anticipated to further enhance text mining. Meanwhile, it's more essential to consider what else can be achieved with LLMs and how we can develop more effective LLMs for chemistry and materials science. For instance, LLMs have the potential to revolutionize predictive modelling by incorporating the extensive "fuzzy knowledge" encapsulated within scientific literature, especially in chemistry and drug discovery. By combining empirical results with documented knowledge, LLMs could assist chemists identify patterns in experiments that might otherwise be missed, predict properties of compounds and outcomes of reactions, and even generate new chemical hypotheses and theories. Furthermore, the integration of LLMs' comprehension with specialized tools could substantially lower the barrier of chemists to use these tools throughout the entire workflow, thanks to interactive interfaces in natural language. Future research could investigate how to merge formatted laboratory data with the wealth of information in scientific literature and develop the multimodal capability to enrich specific domain knowledge for LLMs. This endeavour will require a sustained, long-term effort.

Conclusions

In this work, we have demonstrated the effectiveness of fine-tuning LLMs in chemical text mining. We conducted five complex tasks: compound entity recognition, reaction role labelling, MOF synthesis information extraction, NMR data extraction, and the transformation of reaction procedures to action sequences. Chemical text mining remains a challenging professional domain when leveraging language model mining, even with prompt engineering. However, LLMs that are fine-tuned with appropriate annotations can produce structured outputs that perfectly fulfil human requirements not easily expressed in natural language. This feature fully utilizes their natural language understanding and formatting capability. Using chemical text mining as an example, this study provides guidance on fine-tuning of LLMs to serve as universal knowledge extraction toolkits. These toolkits can be easily extended for automated extraction from documents and rule-based formatted transformations. Our work lays the groundwork for the applications of LLMs in information extraction within the chemical domain, which will catalyse data-driven innovations in chemical and materials science.

Methods

Dataset preparation

For the Paragraph2Compound task, we compiled an automatically annotated dataset. This dataset is based on the publicly accessed USPTO subset extracted by Lowe *et al.*,[31,32] and includes millions of chemical reaction paragraphs from patents, each paired with compound tags. We used regular expressions to identify compound labels within each paragraph, separating them with the "|" symbol based on their sequential occurrence in the paragraph. For the Paragraph2RXNRole task, we used the manually annotated dataset by Guo *et al.*,[8] following the same data partitioning strategy. We transformed the data from the BIO-token classification format into a sequence-to-sequence format using the annotation scheme "<Role*compound*Role>". We processed paragraphs containing multiple central products and related reactions into several input and output pairs. For the Paragraph2MOFInfo task, we manually checked and re-annotated the raw data of Zheng *et al.*,[14] transforming them into a sequence-to-sequence format. This dataset comprises MOF synthesis paragraphs, extraction by ChatGPT, and human-evaluated answers. For the Paragraph2NMR task, we manually curated a dataset of 600 high-quality annotations. These were mainly sourced from various literature studies on PubMed to ensure a wide diversity. The task aims to extract information such as the IUPAC name, experimental conditions, including the frequency and solvent, and chemical shift data from both ^{1}H NMR and ^{13}C NMR spectra. For the Paragraph2Action task, we utilized the hand-annotated dataset by Vaucher *et al.*, employing the same data partitioning strategy. This dataset is derived from the Pistachio dataset by NextMove software.[33] The details of datasets used for the five chemical text mining tasks are listed in Table S1.†

Prompt-only ChatGPT

Prompt-only interaction enables users to efficiently communicate with large language models through simple prompts. This guides the model to produce relevant responses without further training. In a zero-shot scenario, the model generates responses using only a descriptive prompt and its pre-trained knowledge. However, in a few-shot approach, the model uses a small number of examples to improve its understanding and responses. To maximize the performance, we selected diverse examples and ensured a large number of tokens. We interacted with ChatGPT using API keys and employed model versions GPT-3.5-turbo-0613 and GPT-4-0613. The zero-shot and few-shot prompts for chemical text mining tasks can be found in Fig. S2–S8.†

Fine-tuning ChatGPT

Since late August 2023, supervised fine-tuning capabilities have been available for the GPT-3.5-turbo model.[34] The aim is to enhance performance in specific scenarios customized based on private data. In this study, we fine-tuned the GPT-3.5-turbo-0613 model for chemical text mining scenarios on five tasks. When discussing the performance in the Comparison of different methods for chemical text mining section, we fine-tuned the latest GPT-3.5-turbo-0125 model for fair comparison, which expanded the context length to 16 K and supported fine-tuning as well. We formatted the data into jsonl and uploaded them to OpenAI's cloud servers, and then initiated fine-tuning jobs. Once the training was complete, the fine-tuned GPT-3.5-turbo model was ready for inference. API keys were requisite throughout the training and inference procedures. Fine-tuning for the GPT-4-turbo model is not available now and is highly expected in the future.

Fine-tuning open-source language models

We selected the most widely used and representative generative pre-trained language models such as Mistral,[17] Llama3,[18] Llama2,[19] T5,[20] and BART.[21] These serve as baselines for a comprehensive comparison with the fine-tuned ChatGPT across five chemical text mining tasks. Considering performance, efficiency, and hardware resource constraints, we used full parameter fine-tuning for Mistral-7b-instruct-v0.2 and Llama3-8b-instruct on 4 × 40 GB A100, and full parameter fine-tuning for BART-base and T5-base on 1 × 40 GB A100. We applied multitask-learning to BART and T5 in the Paragraph2MOFInfo task and Paragraph2NMR task due to their limitations in generating multi-attribute long sentences (Fig. S9 and S10†), aiming to enhance their performance. This approach significantly improved their performance. For Llama2, we used Q-LoRA[35] to efficiently fine-tune llama2-13b-chat on 1 × 40 GB A100. This method maintains most of the performance of full parameter fine-tuning while significantly reducing computational demands. We used vllm[36] to speed up the inference of LLMs such as Mistral-7b-instruct-v0.2, Llama3-8b-instruct, and Llama2-13b-chat, which is tens of times faster than Hugging Face's pipeline. The inference of all fine-tuned models can run on 1 × 40 GB A100. To ensure optimal performance, we adjusted hyperparameters such as learning rates, lora_r, and lora_alpha during the fine-tuning process of baseline models (Table S2†). The hardware resources, memory cost, and runtimes of fine-tuning are provided for reference (Table S3†). More details of training, pre-processing, and post-processing can be found in the ESI.†

Metrics for evaluation

Since fine-tuning ChatGPT does not allow for early stopping based on optimal validation loss, we report the performances of all models at the best epoch selected from the evaluation set for fair comparison. Given the task specifics, we use metrics including precision, recall, and F1 score for evaluating entity-level performance. For sentence-level performance assessment, we use Levenshtein similarity, exact match accuracy, partial accuracy, and a modified BLEU score.

Data availability

All data and code of this work are available at GitHub: https://github.com/zw-SIMM/SFTLLMs_for_ChemText_Mining to allow replication of processing, fine-tuning and evaluation. All concrete values of performance in figures are listed in Section 5 of the ESI.†

Author contributions

W. Z., J. C. X., Z. Y. F., and M. Y. Z. conceived the idea. M. Y. Z. and Z. Y. F. designed the research. W. Z., Q. G. W., and Z. M. H. implemented the codes. W. Z., Q. G. W., X. T. K., J. C. X., S. K. N., and Z. Y. F. collected, annotated, and processed the training data. D. H. C., B. Y. N., Q. S., and X. T. L. checked the data. Y. M. L., M. A. C., R. Z. Z., Y. T. W., and L. H. Z. benchmarked the models. W. Z. wrote the initial draft. M. Y. Z., Z. Y. F. and Z. P. X. reviewed and refined the article. All authors contributed to the analysis of the results. All authors read and approved the final manuscript.

Conflicts of interest

There are no conflicts to declare.

Acknowledgements

We thank all contributions of the open-source community on LLMs. We appreciate Yaghi's group for guiding in ChatGPT prompt engineering for chemistry tasks. This work was supported by the National Natural Science Foundation of China (T2225002 and 82273855 to M. Y. Z. and 82204278 to X. T. L.), the National Key Research and Development Program of China (2022YFC3400504 to M. Y. Z.), the SIMM-SHUTCM Traditional Chinese Medicine Innovation Joint Research Program (E2G805H to M. Y. Z.), the Shanghai Post-doctoral Excellence Program (2023693 to Z. Y. F.) and the Shanghai Municipal Science and Technology Major Project.

References

1 A. C. Vaucher, F. Zipoli, J. Geluykens, V. H. Nair, P. Schwaller and T. Laino, Automated extraction of chemical synthesis actions from experimental procedures, *Nat. Commun.*, 2020, **11**, 3601.
2 M. Suvarna, A. C. Vaucher, S. Mitchell, T. Laino and J. Pérez-Ramírez, Language models and protocol standardization guidelines for accelerating synthesis planning in heterogeneous catalysis, *Nat. Commun.*, 2023, **14**, 7964.
3 S. H. M. Mehr, M. Craven, A. I. Leonov, G. Keenan and L. Cronin, A universal system for digitization and automatic execution of the chemical synthesis literature, *Science*, 2020, **370**, 101–108.
4 S. Steiner, J. Wolf, S. Glatzel, A. Andreou, J. M. Granda, G. Keenan, T. Hinkley, G. Aragon-Camarasa, P. J. Kitson and D. Angelone, Organic synthesis in a modular robotic system driven by a chemical programming language, *Science*, 2019, **363**, eaav2211.

5 T. Ha, D. Lee, Y. Kwon, M. S. Park, S. Lee, J. Jang, B. Choi, H. Jeon, J. Kim and H. Choi, AI-driven robotic chemist for autonomous synthesis of organic molecules, *Sci. Adv.*, 2023, **9**, eadj0461.

6 M. C. Swain and J. M. Cole, ChemDataExtractor: a toolkit for automated extraction of chemical information from the scientific literature, *J. Chem. Inf. Model.*, 2016, **56**, 1894–1904.

7 J. Mavracic, C. J. Court, T. Isazawa, S. R. Elliott and J. M. Cole, ChemDataExtractor 2.0: autopopulated ontologies for materials science, *J. Chem. Inf. Model.*, 2021, **61**, 4280–4289.

8 J. Guo, A. S. Ibanez-Lopez, H. Gao, V. Quach, C. W. Coley, K. F. Jensen and R. Barzilay, Automated chemical reaction extraction from scientific literature, *J. Chem. Inf. Model.*, 2021, **62**, 2035–2045.

9 C. M. Castro Nascimento and A. S. Pimentel, Do Large Language Models Understand Chemistry? A Conversation with ChatGPT, *J. Chem. Inf. Model.*, 2023, **63**, 1649–1655.

10 T. M. Clark, E. Anderson, N. M. Dickson-Karn, C. Soltanirad and N. Tafini, Comparing the Performance of College Chemistry Students with ChatGPT for Calculations Involving Acids and Bases, *J. Chem. Educ.*, 2023, **100**, 3934–3944.

11 T. Guo, K. Guo, Z. Liang, Z. Guo, N. V. Chawla, O. Wiest and X. Zhang, *arXiv*, 2023, preprint, arXiv:2305.18365, DOI: **10.48550/arXiv.2108.09926**.

12 Z. Ji, N. Lee, R. Frieske, T. Yu, D. Su, Y. Xu, E. Ishii, Y. J. Bang, A. Madotto and P. Fung, Survey of hallucination in natural language generation, *ACM Comput. Surv.*, 2023, **55**, 1–38.

13 Y. Zhang, Y. Li, L. Cui, D. Cai, L. Liu, T. Fu, X. Huang, E. Zhao, Y. Zhang and Y. Chen, *arXiv*, 2023, preprint, arXiv:2309.01219, DOI: **10.48550/arXiv.2309.01219**.

14 Z. Zheng, O. Zhang, C. Borgs, J. T. Chayes and O. M. Yaghi, ChatGPT Chemistry Assistant for Text Mining and the Prediction of MOF Synthesis, *J. Am. Chem. Soc.*, 2023, **145**, 18048–18062.

15 L. Patiny and G. Godin, *ChemRxiv*, 2023, DOI: **10.26434/chemrxiv-2023-05v1b-v2**.

16 Q. Chen, H. Sun, H. Liu, Y. Jiang, T. Ran, X. Jin, X. Xiao, Z. Lin, H. Chen and Z. Niu, An Extensive Benchmark Study on Biomedical Text Generation and Mining with ChatGPT, *Bioinformatics*, 2023, btad557.

17 A. Q. Jiang, A. Sablayrolles, A. Mensch, C. Bamford, D. S. Chaplot, D. d. l. Casas, F. Bressand, G. Lengyel, G. Lample and L. Saulnier, *arXiv*, 2023, preprint, arXiv:2310.06825, DOI: **10.48550/arXiv.2310.06825**.

18 *Llama3*, **https://llama.meta.com/llama3/**, accessed April 26, 2024.

19 H. Touvron, L. Martin, K. Stone, P. Albert, A. Almahairi, Y. Babaei, N. Bashlykov, S. Batra, P. Bhargava and S. Bhosale, *arXiv*, 2023, preprint, arXiv:2307.09288, DOI: **10.48550/arXiv.2307.09288**.

20 C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li and P. J. Liu, Exploring the limits of transfer learning with a unified text-to-text transformer, *J. Mach. Learn. Res.*, 2020, **21**, 5485–5551.

21 M. Lewis, Y. Liu, N. Goyal, M. Ghazvininejad, A. Mohamed, O. Levy, V. Stoyanov and L. Zettlemoyer, *arXiv*, 2019, preprint, arXiv:1910.1346, DOI: **10.48550/arXiv.1910.13461**.

22 D. F. Nippa, A. T. Müller, K. Atz, D. B. Konrad, U. Grether, R. E. Martin and G. Schneider, *ChemRxiv*, 2024, preprint, DOI: **10.26434/chemrxiv-2023-nfq7h-v2**.

23 S. M. Kearnes, M. R. Maser, M. Wleklinski, A. Kast, A. G. Doyle, S. D. Dreher, J. M. Hawkins, K. F. Jensen and C. W. Coley, The open reaction database, *J. Am. Chem. Soc.*, 2021, **143**, 18820–18826.

24 R. Mercado, S. M. Kearnes and C. W. Coley, Data sharing in chemistry: lessons learned and a case for mandating structured reaction data, *J. Chem. Inf. Model.*, 2023, **63**, 4253–4265.

25 *SciFinder*, **https://scifinder-n.cas.org**, accessed August 29, 2023.

26 *Reaxys*, **https://www.reaxys.com**, accessed August 29, 2023.

27 J. Xiong, X. Liu, Z. Li, H. Xiao, G. Wang, Z. Niu, C. Fei, F. Zhong, G. Wang and W. Zhang, αExtractor: a system for automatic extraction of chemical information from biomedical literature, *Sci. China: Life Sci.*, 2023, **67**, 618–621.

28 Y. Qian, J. Guo, Z. Tu, Z. Li, C. W. Coley and R. Barzilay, MolScribe: Robust Molecular Structure Recognition with Image-to-Graph Generation, *J. Chem. Inf. Model.*, 2023, **63**, 1925–1934.

29 Y. Qian, J. Guo, Z. Tu, C. W. Coley and R. Barzilay, RxnScribe: A Sequence Generation Model for Reaction Diagram Parsing, *J. Chem. Inf. Model.*, 2023, **63**, 4030–4041.

30 D. M. Wilary and J. M. Cole, ReactionDataExtractor 2.0: a deep learning approach for data extraction from chemical reaction schemes, *J. Chem. Inf. Model.*, 2023, **63**, 6053–6067.

31 D. Lowe, *Chemical reactions from US patents (1976-Sep2016)*, **https://figshare.com/articles/dataset/Chemical_reactions_from_US_patents_1976-Sep2016_/5104873**, accessed August 29, 2023, DOI: **10.6084/m9.figshare.5104873.v1**.

32 D. M. Lowe, PhD thesis, University of Cambridge, 2012.

33 *Pistachio*, **https://www.nextmovesoftware.com/pistachio.html**, accessed August 22, 2023.

34 A. Peng, M. Wu, J. Allard, L. Kilpatrick and S. Heidel, *GPT-3.5 Turbo fine-tuning and API updates*, **https://openai.com/blog/gpt-3-5-turbo-fine-tuning-and-api-updates**, accessed August 22, 2023.

35 T. Dettmers, A. Pagnoni, A. Holtzman and L. Zettlemoyer, *arXiv*, 2023, preprint, arXiv:2305.14314, DOI: **10.48550/arXiv.2305.14314**.

36 W. Kwon, Z. Li, S. Zhuang, Y. Sheng, L. Zheng, C. H. Yu, J. Gonzalez, H. Zhang and I. Stoica, *presented in part at the Proceedings of the 29th Symposium on Operating Systems Principles*, Koblenz, Germany, 2023.