BioKG: a comprehensive, high-quality biomedical knowledge graph for AI-powered, data-driven biomedical research

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Abstract:

To cope with the rapid growth of scientific publications and data in biomedical research, knowledge graphs (KGs) have emerged as a powerful data structure for integrating large volumes of heterogeneous data to facilitate accurate and efficient information retrieval and automated knowledge discovery (AKD). However, transforming unstructured content from scientific literature into KGs has remained a significant challenge, with previous methods unable to achieve human-level accuracy. In this study, we utilized an information extraction pipeline that won first-place in the LitCoin NLP Challenge to construct a large-scale KG using all PubMed abstracts. The quality of the large-scale information extraction rivals that of human expert annotations, signaling a new era of automatic, high-quality database construction from literature. Our extracted information markedly surpasses the amount of content in manually curated public databases. To enhance the KG's comprehensiveness, we integrated relation data from 40 public databases and relation information inferred from high-throughput genomics data. The comprehensive KG enabled rigorous performance evaluation of AKD, infeasible in previous studies. We designed an interpretable, probabilistic-based inference method to identify indirect causal relations and achieved unprecedented results for drug target identification and drug repurposing. Taking lung cancer as an example, we found that 40% of drug targets reported in literature could have been predicted by our algorithm about 15 years ago in a retrospective study, demonstrating that substantial acceleration in scientific discovery could be achieved through automated hypotheses generation and timely dissemination. A cloud-based platform was developed for academic users to freely access this rich structured data and associated tools.

Introduction

The sheer volume of information produced daily in scientific literature, expressed in natural languages, makes it impractical to manually read all publications, even within relatively narrow research areas. Additionally, advances in high-throughput technologies have led to the creation of enormous quantities of research data, much of which remains underutilized in various databases. This information explosion poses a major challenge for researchers to identify and develop new ideas using all the available data. Automated knowledge discovery (AKD, a.k.a. automated hypothesis generation) can help mitigate this problem by automating the process of data analysis, identifying patterns, and generating new insights and hypotheses. In recent years, knowledge graphs (KGs) have been proposed as a powerful data structure for integrating heterogeneous data and for AKD(*1–7*). KGs, with entities as nodes and their relationships as edges, represent a structured depiction of human knowledge, which facilitates efficient and accurate information retrieval. Graph algorithms can be employed on KGs to infer potential new relationships as plausible hypotheses between known entities.

Computational construction of KGs from unstructured text entails two steps: named entity recognition (NER) to identify key biological entities and relation extraction (RE) to extract relationships among entities. Historically, NER and RE have been collectively referred to as information retrieval tasks. Early automated methods mainly fell into two categories: rule-based and machine learning-based. The rule-based approach systematically extracted specific data based on predefined rules (*8–13*), while the machine learning-based approaches inferred rules from annotated data usually with much better recall and overall performance (*14–29*). The advent of machine learning led to more sophisticated methods that leveraged semantic information and sentence structure, resulting in significant improvements in information extraction effectiveness(*19, 22*). However, a gap remained compared to human proficiency.

The emergence of deep learning models has allowed for more nuanced utilization of information, such as semantic content and grammatical structures. By expanding the use of features and enhancing expressive capabilities, deep models have significantly improved the overall effectiveness of information

extraction(*30–42*). Recently, the technique of pretraining and large language models have garnered considerable attention, expanding both model complexity and the amount of training data, and achieving remarkable progress in information retrieval tasks(*41*, *43–54*). This was evidenced by the significant results in the BioCreative VII Challenge in 2021, where finetuning BERT-based models was widely used and the top performance closely matched human annotator performance. Subsequently, a highly advanced series of pretrained models, like GPT-4, emerged(*55–57*). These models have been proven to outperform humans in several tasks, marking a notable advancement in the field.

To facilitate the methodology development and identification of the most effective methods for KG construction, NIH organized the LitCoin natural language processing (NLP) challenge between Nov 2021 and Feb 2022. Our team, JZhangLab@FSU, participated in the challenge and won first-place. In the LitCoin NLP Challenge dataset, six common biological entity types were annotated: diseases, genes/proteins, chemical compounds, species, genetic variants, and cell lines. Eight relation types were also annotated for the entities: association, binding, comparison, conversion, cotreatment, drug interaction, positive correlation, and negative correlation. These entity types and relations are highly relevant in translational research and drug discoveries.

In this study, we applied the information retrieval pipeline we developed for the LitCoin NLP Challenge to all PubMed abstracts (with a cutoff date in May 2022) to construct a large-scale Biomedical Knowledge Graph (BioKG). Manual verification showed that this pipeline has achieved accuracy at the level of a human annotator. Causal relations are essential for automated knowledge discovery. However, the LitCoin dataset did not annotate causal (direction) information. We annotated the directions for the relations in the LitCoin dataset and trained a model to predict the direction of relations. This allows us to construct a causal knowledge graph (CKG) capable of making indirect causal inferences.

To further enhance the coverage of BioKG, we integrated relation data from 40 public databases and relations inferred from high-throughput genomics datasets, making it the most comprehensive, high quality biomedical knowledge graph to date.

To make causal inferences among the entities that are not directly connected in the KG, we designed a probabilistic based approach, probabilistic semantic reasoning (PSR). PSR is highly interpretable as it directly infers indirect relations using direct relations through straightforward reasoning principles.

Knowledge graphs have become instrumental in automated knowledge discovery (AKD)(*7*, *58–60*), particularly in the domain of drug repurposing (*61–65*). Historically, drug repurposing research primarily centered around individual diseases or a limited set of drugs. A significant challenge has been to comprehensively assess the effectiveness of these studies, especially when determining all the therapeutic associations of a particular disease or drug as such efforts require thorough search of literature. However, by harnessing a comprehensive knowledge graph that encompasses all PubMed abstracts, it is plausible to believe that most established drug-disease associations have been documented at least once. This resource empowers us to assess the efficacy of drug repurposing studies on an unprecedented scale. In our investigation, we undertook drug repurposing for ten diseases lacking adequate treatments and analyzed ten prevalent drugs. For each repurposing objective, we extracted all documented therapeutic associations, enabling us to measure recall and the observed positive rate (OPR), infeasible in prior drug repurposing research.

Another drug repurposing exercise we performed was real-time drug repurposing (RTDR), exemplified using COVID-19 to mimic an authentic pandemic setting. Beginning in March 2020, monthly RTDR assessments were conducted based on the known drug targets for COVID-19 at each juncture. This approach allowed us to track the validation rate of our initial predictions. RTDR was previously unattainable due to the immense challenge of manually vetting literature for a plethora of drug candidates.

Lastly, our application of PSR to BioKG underscored the knowledge graph's potency in two pivotal drug discovery domains: drug target identification and drug repurposing. PSR surfaced numerous viable candidates, buttressed by substantial literature evidence connecting the drug (or drug target) and disease

entities. This level of interpretability is invaluable when determining the necessity of subsequent research endeavors.

Results

Constructing a large-scale and high-quality biomedical knowledge graph (BioKG)

In constructing BioKG, we processed over 34 million PubMed abstracts, resulting in 10,686,927 unique entities and 30,758,640 unique relations. The performance of the method in the LitCoin Challenge can be found in supplementary materials (Table S1). We incorporated entity normalization into our pipeline, as this was not a component of the LitCoin challenge (see Supplementary Materials for more details).

We evaluated the accuracy of our large-scale relation extraction (RE) and our novelty prediction results, using a sample of 50 randomly chosen PubMed abstracts (refer to Table S2). The results indicate that the performance of our information extraction rivals that of human annotations, with a more in-depth analysis available in the Supplementary Materials.

We further integrated relation data from 40 public databases and from analysis results of some commonly used public genomics datasets (Supplementary Materials). After data integration, BioKG has 11,479,285 unique entities across 12 types (e.g., genes, diseases, chemical compounds) and 42,504,077 relations from 52 types (e.g., associations, positive correlation, cotreatment, etc.).

Figure 1A shows the numbers of PubMed abstracts containing one or more of the four major types of entities: diseases, genes, chemicals, and sequence variants. It is evident that diseases are the most common topic with over 20 million articles referencing at least one disease entity, and nearly half of these focusing exclusively on diseases. In contrast, gene mentions often coexist with other entities, such as chemicals and diseases. Figure 1B depicts the numbers of PubMed abstracts containing one or more of the five major types of relations, offering insight into the distribution of topics in biomedical research.

We plotted $p(k)$ vs k, where k is the degree of an entity in BioKG and $p(k)$ is the probability of an entity having degree k (Supplementary Materials, Figure S1).

Figure 1C compares the relations extracted from PubMed with those from databases and LitCoin dataset. There is a clear difference between the LitCoin dataset and general PubMed abstracts, as the former contains more relation in each abstract, especially those involving sequence variant entities(*66*), which explained the performance difference of our pipeline on these two datasets. Relations from PubMed and public databases are also quite complimentary to each other.

Figure 1D compares the numbers of relations for five types of entity pairs from all the public databases integrated in BioKG, those extracted from PubMed, and the numbers extracted if we use a simple co-occurrence rule, which considers two entities having a relation if they co-occur in an abstract. On one hand, BioKG has significantly more numbers of relations than those from public databases (the y-axis shows Log(count)). On the other hand, numbers of co-occurrences are much larger than relations extracted using our LitCoin pipeline, indicating a substantial noise reduction by explicitly extracting relations from literature as compared to retrieval using keywords.

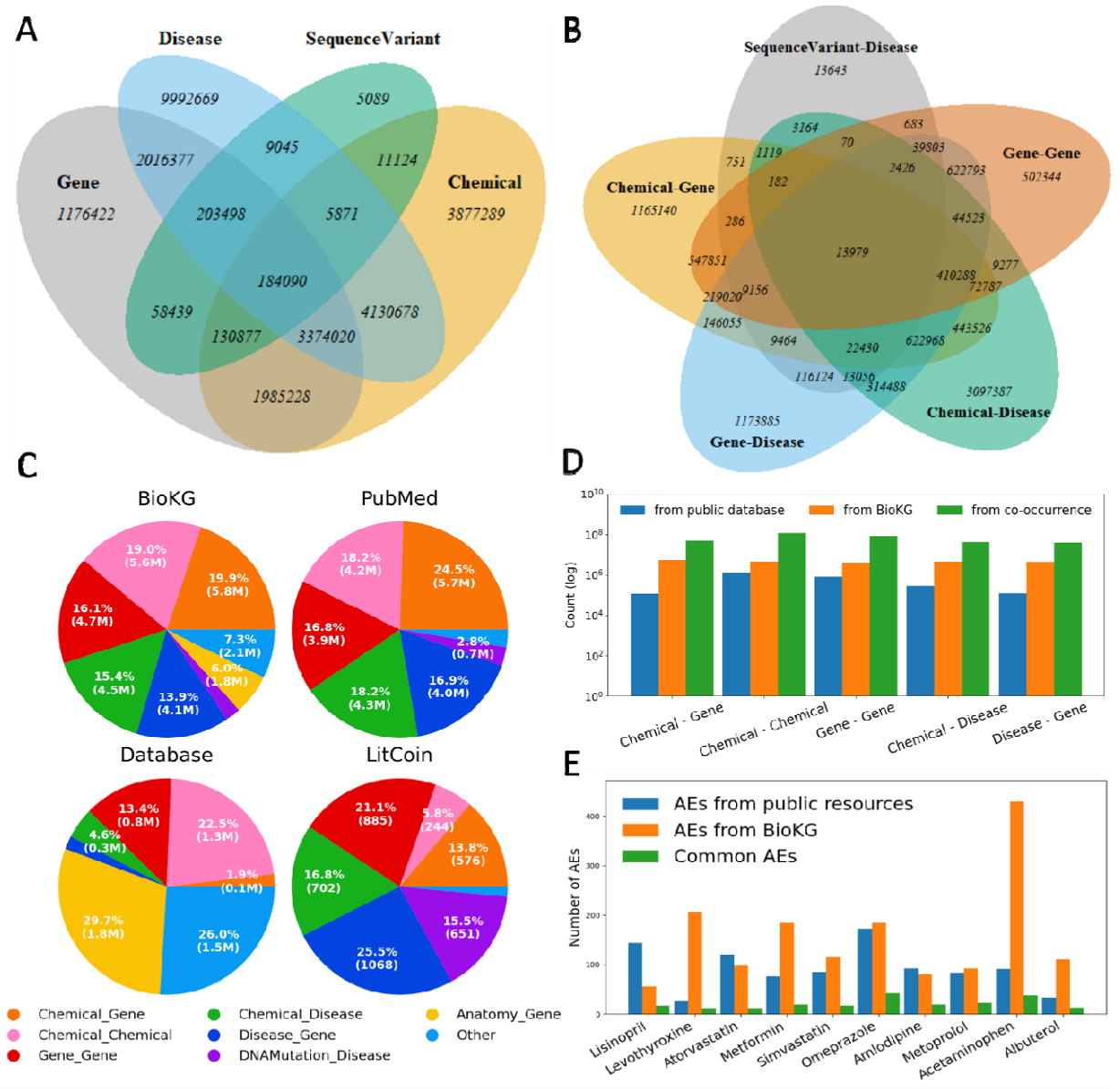

Figure 1. A. Venn diagram for the numbers of PubMed articles containing certain types of entities; **B.** Venn diagram for the numbers of PubMed articles containing certain types of relations; **C.** The composition of relations in BioKG, PubMed abstracts, public databases, and LitCoin dataset; **D.** The numbers of relations between entity types in BioKG compared with 40 public databases combined.

A Case Study in Pharmacovigilance

Drug safety represents a critical component in pharmaceutical development and production processes.

We evaluate the adverse event (AE) information in BioKG by comparing it with those in the OpenFDA

(*67*) and SIDER (*65*) databases for ten well-known drugs. The AE information in BioKG is the positive correlation relation between chemical entities and diseases (including phenotypical features) with direction from chemicals to diseases. Figure 1E shows that BioKG contains significant numbers of AEs not documented in public databases for all the ten drugs (Table S3 in Supplementary Materials). We conducted a manual examination of ten unique AEs for each drug that were in BioKG but absent in the other databases, and found that a majority of these AEs were indeed true, with a precision of 91%. To further validate that we were indeed uncovering new, previously unrecorded AEs, as opposed to identifying synonyms of known AEs, we employed ChatGPT to check for synonyms for an additional layer of verification. We found on average, over 85% of the 100 randomly sampled AEs for the ten drugs were novel findings. This result demonstrated the effectiveness of our literature-based approach for uncovering a significant proportion of AEs overlooked in professional databases. It highlights the challenges of accessing such information without accurate information extraction tools, positioning BioKG as a vital resource in drug safety.

Drug repurposing for Covid-19 using causal knowledge graph

We conducted a retrospective, real-time drug repurposing study for COVID-19 (*68*) spanning from March 2020 to May 2023 (Figure 2) using the PSR algorithm. During this period, we consistently repurposed drugs based on the drug targets reported for COVID-19 between March and June 2020. A candidate drug is defined as one that has a directed path through a gene to COVID-19. Our monthly assessments involved scrutinizing whether these repurposed drugs had been subsequently tested in clinical trials documented on ClinicalTrials.gov or had demonstrated therapeutic efficacy in COVID-19 patients through their mention in PubMed abstracts. It is noteworthy that drugs identified in clinical trials may not always translate into effective treatments for COVID-19. Nevertheless, they serve as valuable hypotheses, aligning with the primary objective of our drug repurposing approach. As shown in **Error! Reference source not found.**A, we were able to identify nearly 200 to 1,400 candidate drugs from our causal KG. Remarkably, one-third of the repurposed drugs identified during the initial two months were

later validated as effective treatments or plausible potential treatments worthy of clinical trials. Importantly, even drugs that did not achieve validation status remain viable hypotheses, warranting further investigation, particularly when existing treatments prove less than optimal.

Figure 2B presents a timeline showcasing the validation of repurposed drugs. Notably, there's a surge in validated drugs during the first year, which subsequently shows a month-to-month decline. This pattern suggests that a majority of the repurposed drugs align with practitioners' assessments. Interestingly, some drugs only received validation in the second or even the third year, hinting that these might not have been as immediately evident or persuasive as those tested earlier. A deeper analysis is warranted to discern any significant variances between drugs validated at different times. The count of drugs validated through publications is on par with those through clinical trials. While numerous drug repurposing studies for COVID-19 exist (*68–71*), as per our understanding, no prior research has as thoroughly validated such a vast quantity of repurposed drugs as we have in this research. These findings underscore our causal KG's proficiency in pinpointing promising drug candidates for specific diseases in real-time scenarios.

We then conducted drug repurposing for COVID-19 in the current timeframe (Figure 2C). We did not exclude drugs already reported as treatments for COVID-19 (direct relations). This was to observe if our repurposing efforts agree with existing treatment choices for COVID-19. Figure 2C displays the top 50 repurposed drugs. Notably, a majority of them (35 out of 50) were known treatments for COVID-19. Among the remaining 15, 14 have been proposed as potential treatments for COVID-19 (citations provided in Supplementary Materials). For each of the drugs, numerous genes were identified that link COVID-19 with the drug. Additionally, each of these relations, whether drug-gene or gene-COVID-19, is supported by one or multiple articles. To our knowledge, none of the previous literature-based COVID-19 repurposing studies has yielded such comprehensive findings.

Drug repurposing for 10 diseases and 10 drugs

To further assess our method's applicability across varied conditions, we extended the drug repurposing to ten diseases that lack satisfactory treatments, and ten commonly prescribed drugs (as

illustrated in Figure 3). Our PSR algorithm identified a vast array of candidates for these drugs and indications. For each drug (or disease) assessed, we calculated both the recall and the observed positive rate (OPR). Historically, these metrics posed challenges in estimation due to the reliance on manual literature searches. Recall is defined as the percentage of known direct relations that were successfully repurposed, while OPR quantifies the percentage of repurposed cases that have reported direct relations. Instead of precision, we opted for OPR, considering that numerous repurposed candidates could be valid prospects awaiting further validation. Impressively, our findings revealed average recall values of 0.91 for disease repurposing and 0.904 for drug repurposing. This exceptional recall rate emphasizes the potency of BioKG coupled with our PSR algorithm in spotlighting viable drug repurposing candidates. Notably, these elevated recall rates were achieved without an excessive number of predictions. The observed OPRs remained commendable at 0.197 for diseases and 0.07147 for drugs. Importantly, a significant proportion of indications repurposed for these drugs are not associated with current treatments in PubMed abstracts. This suggests that certain ailments might still be without treatments, and these widely used drugs could potentially fill those therapeutic gaps.

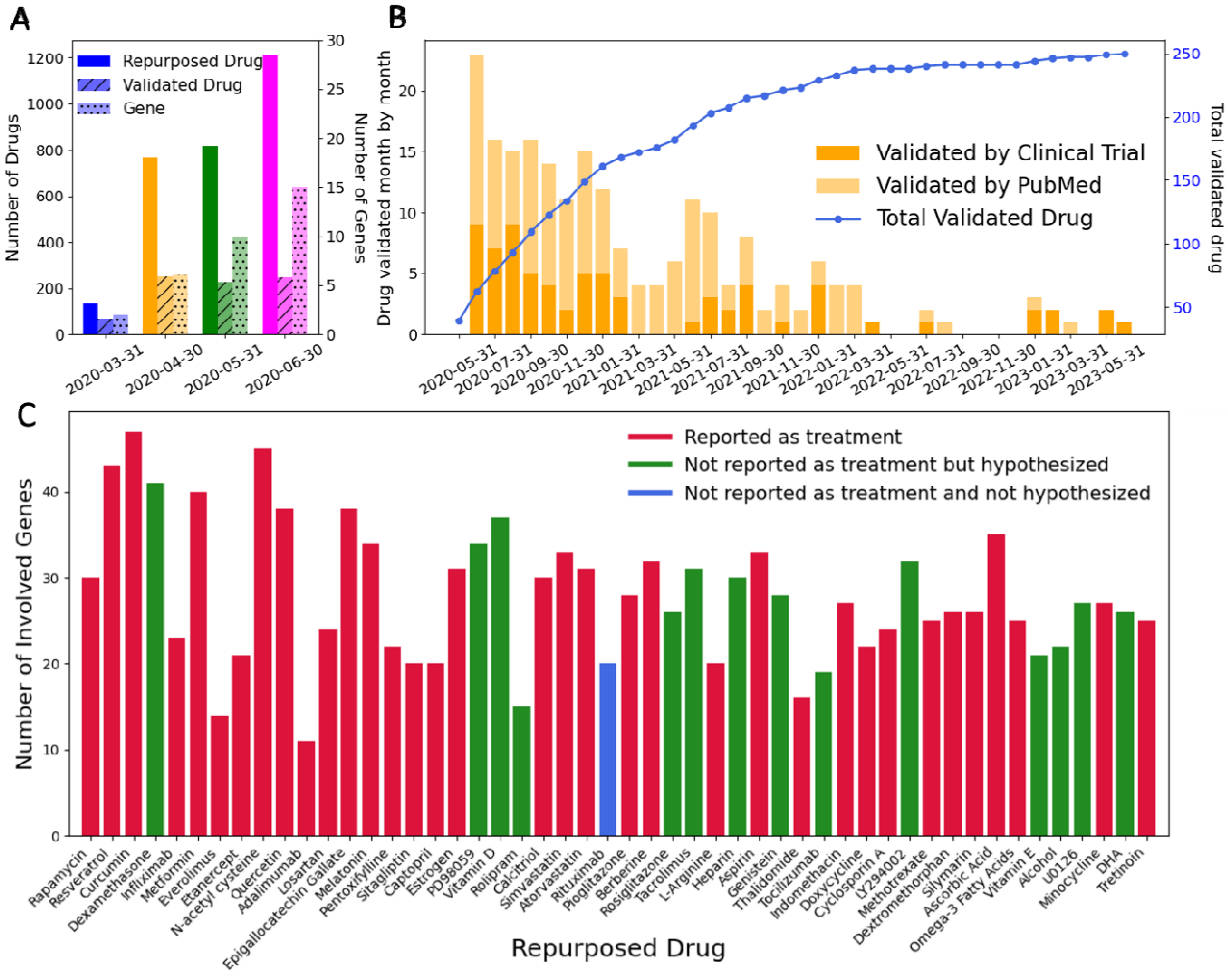

Figure 2. Drug repurposing for COVID-19. **A.** The number of repurposed drugs, number of verified drugs and number of COVID-19 related genes for the first four months of COVID-19 pandemic (March to June 2020); **B.** The number of verified drugs each month for those drugs repurposed for Apr 2020; **C.** The number of genes involved in the drugs repurposed at present time (March 2023). The figure shows top 50 repurposed drugs sorted from left to right with those on the left having higher scores. Almost all the repurposed drugs interact with many genes (height of the bar) that are related to COVID-19. Majority of the drugs were reported as treatment for COVID-19 (35 out of 50). Among those that were not reported as treatments for COVID-19, 14 out of 15 were hypothesized as potential treatment.

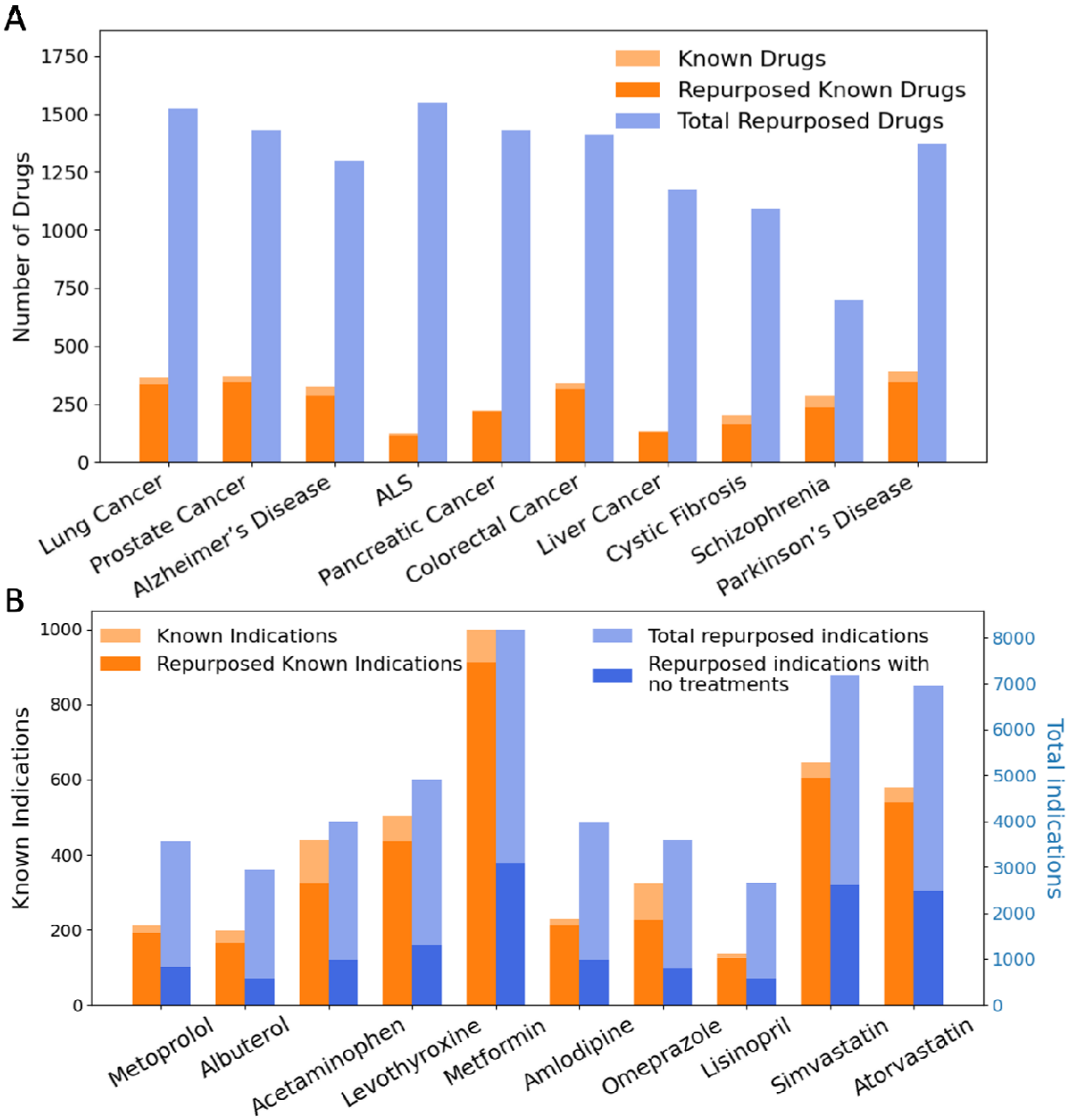

Figure 3. Drug repurposing for 10 diseases and 10 common drugs. Our method identified large numbers of candidates. The known drugs or indications are those extracted from PubMed abstracts, not FDA approved drugs or indications. On average, our method has repurposed more than 90% of the known drugs or indications. **A.** Drug repurposing for 10 diseases without satisfactory treatments; **B.** Drug repurposing for 10 common drugs. Among the repurposed indications, some (dark blue bar) do not have reported treatments in PubMed abstracts, which may be unmet medical needs.

Drug target identification for lung cancer

In addition to drug repurposing, causal knowledge graph serves as a powerful tool for pinpointing potential drug targets (genes) for diseases. These targets are entities not directly linked with the disease in

existing literature but possess an indirect, more subtle, connection through other genes or entities. As a case study to demonstrate the power of BioKG for target identification (TI), we applied PSR to infer indirect relation from genes/proteins to lung cancer. The TI procedure was conducted annually from 1986 to 2009 (Figure 4A and 4B). Notably, since the start of this century, we have consistently proposed no fewer than 100 potential drug targets each year. If a proposed target was later reported as a direct relation with direction from the gene to the disease, we consider the proposed target was validated later. The average recall from 1989 to 2022 is 0.4071 (Figure 4B) and the average OPR from 1988 to 2009 is 0.3237 (Figure 4A). These two metrics were calculated for different time intervals because to calculate recall we need to first predict targets for some years and targets predicted for recent years still need time to be validated. We also calculated the average duration it typically takes for these targets to be validated. Intriguingly, our proposals for potential drug targets precede their appearance in literature from 4.5 to 24 years with a median of 15 years (Figure 4A). If we assume that validating a drug target experimentally takes on average 5 years, then in a hypothetical scenario, BioKG may cut the time from 15 years to 5 if the researchers had known the potential drug targets right after they were predicted and started to confirm them experimentally. With a recall rate exceeding 40% and a lag of 15 years, it's evident that many of our present-day discoveries could have been accelerated, demonstrating the potential of the causal KG for significantly expediting the discovery of new drug targets and new drug development.

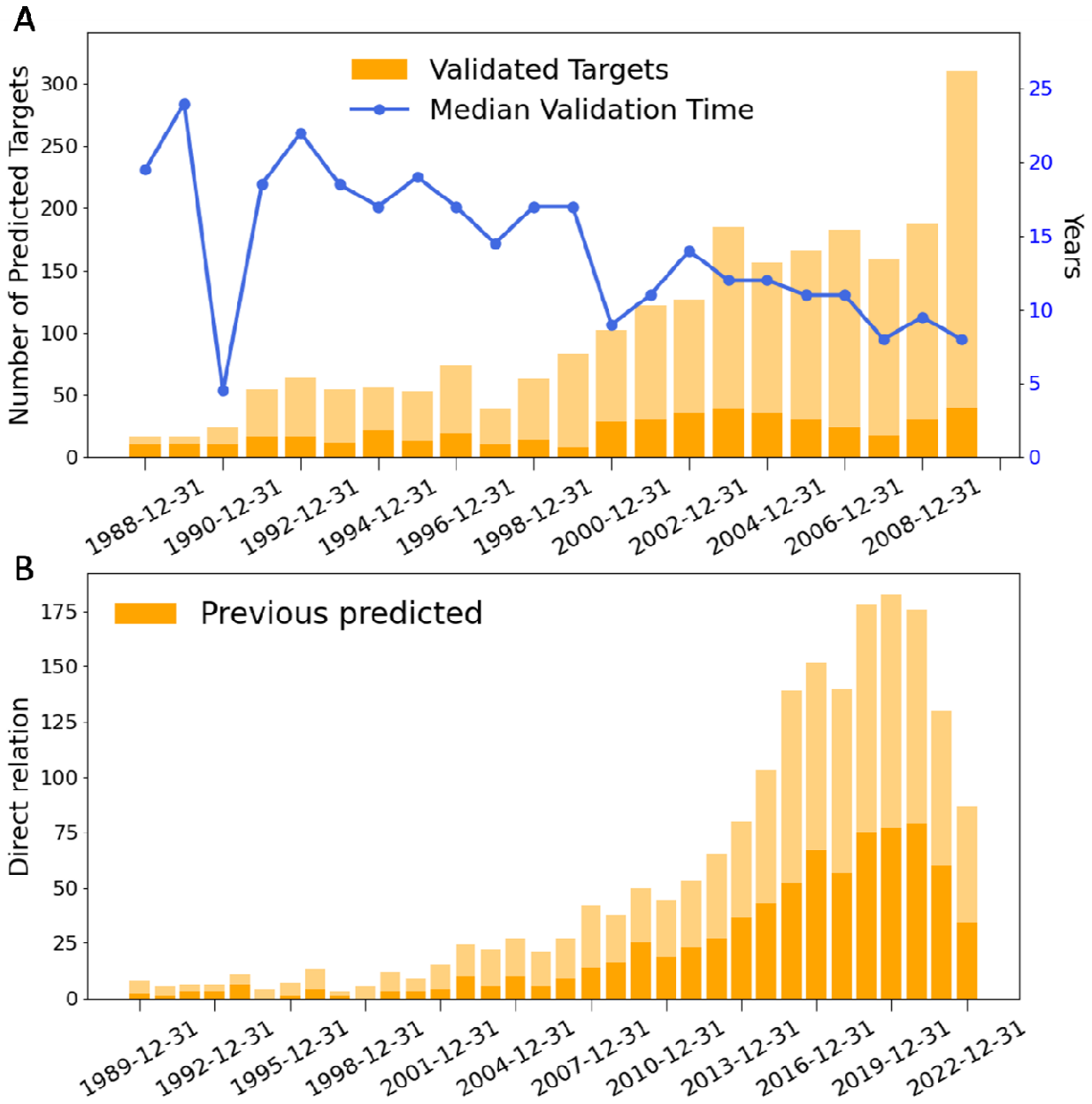

Figure 4. Drug target identification for lung cancer. A. The number of identified targets from year 1988 to 2009. The dark yellow bar shows the number of validated targets. The blue line shows the time it takes to validate the targets for the corresponding years. **B.** The number of drug targets reported in PubMed from the year 1989 to year 2022. The dark yellow bar shows the targets that have been predicted previously.

Discussion

Converting unstructured scientific literature into structured data has been a long-standing challenge in natural language processing (NLP). Successfully addressing this issue has the potential to revolutionize the pace of scientific discoveries. Although there have been numerous studies over the years, computational methods have yet to achieve the precision of manual annotation in relation extraction, posing a significant hurdle. However, the emergence of large language models (LLMs) in recent years has ushered in noteworthy advancements in information extraction through LLM fine-tuning. In this paper, we report the first utilization of a human-level information extraction pipeline to construct a large-scale biomedical knowledge graph by processing all the abstracts in PubMed. By further integrating relation data from 40 public databases and those analyzed from publicly available genomics data, the resulting knowledge graph, dubbed BioKG, stands out as perhaps the most all-encompassing biomedical knowledge graph constructed so far. The coverage of BioKG is much larger than public databases for the relations we have extracted. Construction of a causal knowledge graph and design of an interpretable PSR algorithm allow us to perform automated knowledge discovery very effectively. The exhaustive nature of BioKG allows us to perform research that was infeasible previously. For the first time, we were able to evaluate the performance of automated knowledge discoveries systematically and rigorously by calculating recalls and observed positive rates (OPRs). Without the knowledge of all PubMed abstracts in structured form, one has to perform manual search of the literature, which would not be feasible for a relatively large number of predictions. We summarize the notable advances in this study including some unique BioKG-enabled capabilities in Box 1 (Supplementary Material) and discuss some of them below.

The biomedical research community has traditionally invested significant resources and human effort in knowledge curation through manual annotations. Our research suggests a paradigm shift, leveraging the capabilities of modern large language models (LLMs). By initially producing a limited set of high-caliber labeled data, it's feasible to train an information extraction model that operates at human-level

precision on much larger text datasets. This methodology could notably expand the reach of public databases without compromising data quality.

Utilizing BioKG for knowledge discovery tasks, such as drug repurposing and drug target identification, has yielded a vast array of credible candidates, supported by an unparalleled volume of literature evidence. This underscores the potential of structured knowledge in hastening scientific breakthroughs. In our drug repurposing endeavors for COVID-19, we highlighted BioKG's proficiency in identifying treatments for pandemics, marking it as an indispensable asset for potential future outbreaks. Moreover, with the drug target analysis for lung cancer, we demonstrated that BioKG can notably expedite the drug target identification process for researchers.

Finally, we would like to put our study in the context of the large language models (LLMs) popular in the current NLP research community. While LLMs have showcased exceptional capabilities in understanding and generating natural language, they aren't without shortcomings. A notable limitation is their fixed knowledge cut-off date, which restricts their awareness of the very latest developments. Furthermore, in biomedical research, where precision is crucial, relying solely on LLMs to answer specific questions risks inaccuracies due to their limited knowledge base. Additionally, LLMs possess a propensity to generate text that, while convincingly articulated, may lack factual accuracy. This propensity raises concerns regarding the veracity of answers generated by LLMs, necessitating mechanisms for verification and the production of more substantiated results, possibly with appropriate citations. We believe that integrating knowledge graphs like BioKG with LLMs can effectively mitigate these limitations. To this end, we are actively developing a comprehensive question-answering system, combining BioKG with an open-source LLM.

In the Supplementary Materials, we delve into future research avenues and the challenges we've faced. In summary, BioKG serves as a powerful enabler for more effective and efficient information retrieval and automated knowledge discovery.

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