

SPARK: Harnessing Human-Centered Workflows with Biomedical Foundation Models for Drug Discovery

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Abstract

1 Biomedical foundation models, trained on diverse
2 sources of small molecule data, hold great po-
3 tential for accelerating drug discovery. How-
4 ever, their complex nature often presents a bar-
5 rier for researchers seeking scientific insights and
6 drug candidate generation. SPARK addresses this
7 challenge by providing a user-friendly, web-based
8 interface that empowers researchers to leverage
9 these powerful models in their scientific workflows.
10 Through SPARK, users can specify target proteins
11 and desired molecule properties, adjust pre-trained
12 models for tailored inferences, generate lists of
13 potential drug candidates, analyze and compare
14 molecules through interactive visualizations, and
15 filter candidates based on key metrics (e.g., toxic-
16 ity). By seamlessly integrating human knowledge
17 and biomedical AI models' capabilities through an
18 interactive web-based system, SPARK can improve
19 the efficiency of collaboration between human ex-
20 perts and AI, thereby accelerating drug candidate
21 discovery and ultimately leading to breakthroughs
22 in finding cures for various diseases.

1 Introduction

24 Drug discovery provides the promise of battling diseases
25 that have afflicted humanity, paving the way for new inter-
26 ventions, treatments, and therapies. Recent advancements
27 in biomedical foundation models, fueled by artificial intelli-
28 gence and vast volumes of chemical and biological data, have
29 opened a new avenue for identifying and evaluating potential
30 drug candidates. For instance, such biomedical foundation
31 models, trained on diverse sources of small molecule data,
32 can be used to infer a list of potential drug candidates given
33 biological targets and predict their physicochemical and bio-
34 logical properties.

35 However, one of the major challenges in using biomed-
36 ical foundation models for drug discovery is to seamlessly

integrate the capabilities of biomedical researchers and the
biomedical AI models. AI models are often regarded as
black boxes to human experts due to the intricate neural net-
work architectures, so it is difficult for researchers to com-
prehend their capabilities and use the models to gain scient-
ific insights [Dey *et al.*, 2022]. Furthermore, it often takes a
long-term collaboration among multiple experts to be able to
generate initial candidates, evaluate the outcomes, and then
iteratively refine them. To achieve this goal, we need to de-
sign a human-centered workflow that empowers users to steer
model inferences based on their hypotheses and to translate
outcomes into meaningful biomedical insights.

In this work, we introduce a web-based system, called
SPARK, designed to support user tasks with biomedical foun-
dation models for drug discovery. Our system integrates pre-
trained and fine-tuned models with diverse capabilities, var-
ious open-source analysis toolkits, and interactive visualiza-
tions into a cohesive workflow. It allows researchers to spec-
ify target proteins, adjust model parameters, and set inclu-
sion criteria for the generated molecules by combining in-
teractive visualization tools on the frontend with biomedical
models on the backend. Our system aims to facilitate an AI-
powered, human-centered approach to drug discovery, accel-
erating research efforts within the AI and biomedical com-
munities. This can ultimately foster the development of ad-
vanced AI models for drug discovery and the identification
of novel drug candidates, particularly for neglected diseases
awaiting effective treatments.

2 Design of SPARK

In this section, we introduce user workflows and the design
of individual components of the system. An illustration of
the system is displayed in Figure 1. A demonstration video is
available: <https://vimeo.com/93777860>

2.1 User Workflows and System Overview

Before conducting preclinical and clinical development in
vivo or in vitro, identifying new drug candidates computa-

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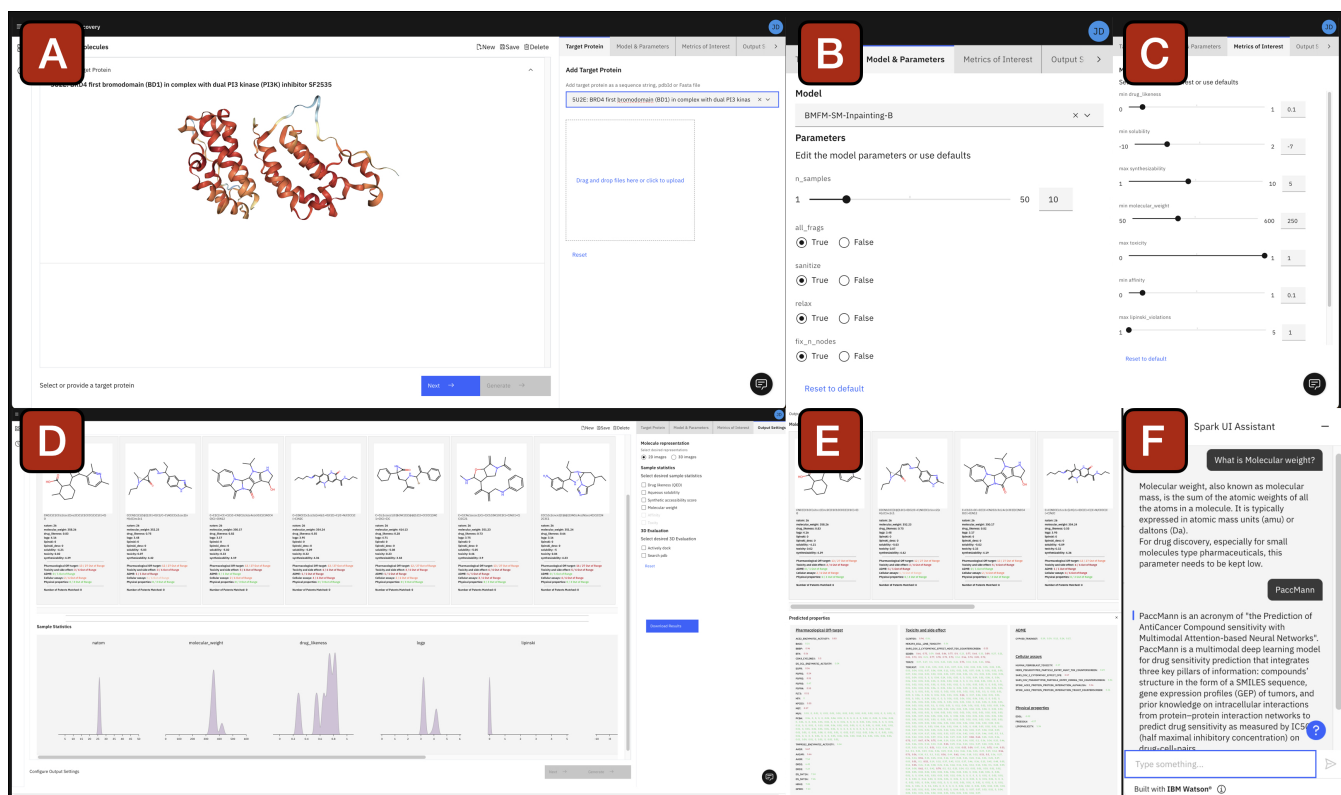


Figure 1: Overview of the system SPARK. (A) Users select target proteins, (B) adjust parameters of models, (C) specify desired ranges for metrics of interest, and (D) analyze generated molecules that fit the criteria. (E) Users can expand the results to view the details of predicted properties and (F) they can ask questions about molecules, chemistry, and small molecule foundation models on a chatbot.

tionally usually consists of two stages: 1) Generating hypotheses: scientists first develop a mechanistic understanding of the disease and identify potential protein targets that could be modulated to treat it; 2) Finding effective molecules: Next, scientists search for molecules that effectively interact with the chosen targets and ultimately cure the disease. Biomedical foundation models can assist in this process by generating molecular candidates for given protein targets. However, the generated candidates may not always be satisfactory. In such cases, users can refine the model parameters to generate new batches of candidates for further evaluation. Specifically, these molecules must also meet specific requirements like low toxicity and high solubility to be viable as pharmaceutical drugs. Fine-tuned models can predict these properties, enabling visualization and detailed analysis to assess suitability. Throughout this process, users may have questions about biomedical concepts, models, and the system itself. SPARK facilitates exploration and decision-making in the computational drug discovery process by integrating biomedical foundation models for generation and prediction with user-friendly interfaces and interactive visualizations.

2.2 Target Protein Selection

To start the drug discovery process, users first decide on one protein from the database. The database includes protein samples that are populated from the Protein Data Bank (PDB). Users may also directly upload their target protein sequences in the FASTA file format. Once users click on one

protein, the main view shows the 3-dimensional structure of the protein. The 3D representation of the target protein, implemented via NGL Viewer [Rose and Hildebrand, 2015], allows users to interactively navigate the protein structure using panning and zooming as Figure 1 (A) shows. By using the view, users can inspect the structural characteristics and speculate docking results for small molecule candidates.

2.3 Models & Parameters Refinement

Once the protein target is determined, users move to the next step to choose biomedical foundation models and their parameter conditions. The system integrates several small molecule foundation models, such as PaccMann within GT4SD [Cadow *et al.*, 2020; Manica *et al.*, 2023], a MolFormer-inspired model [Ross *et al.*, 2022; Belgodere *et al.*, 2022] trained on drug-like molecules with diffusion architectures [Schneuing *et al.*, 2022]. To enable API requests from users, we used a microservices architecture, called Caikit open source¹, on the backend to manage the biomedical foundation models. The weights of the previously trained models are stored as checkpoints (files) in the web server. When users select a model on the website, they are prompted to adjust the values of model parameters for inferences as Figure 1 (B) shows. The kinds of parameters vary among models, such as the number of generated samples and temperature. Users can update the parameters by adjusting

¹<https://github.com/caikit/caikit>

125 the number of generated samples from 10 to 50, for instance.

126 2.4 Metrics of Interest Specification

127 In the next step, users can specify value ranges for metrics of
128 interest so that the generated molecules meet user-specified
129 inclusion criteria. The metrics of interest include properties
130 of molecules that are important to be used as pharmaceutical
131 drugs, such as affinity, drug-likeness score (QED), lipinski
132 score, synthetic accessibility score, molecular weight, LogP,
133 aqueous solubility, and toxicity, as illustrated in Figure 1 (C).
134 For instance, it is important to estimate the ease of synthe-
135 sis through synthetic accessibility score so that scientists can
136 virtually screen and prioritize molecular compounds for rapid
137 experiments and drug discovery. The constraints specified
138 with slider input on the user interface are then used to filter
139 the generated molecules that do not meet the conditions.

140 2.5 Visual Analysis of Generated Molecules and 141 Their Predicted Properties

142 With all user inputs provided, the biomedical foundation
143 model generates a list of small molecule candidates. Subse-
144 quently, the fine-tuned models predict the properties of each
145 generated molecule. The combined results are shown as two
146 visualizations: 1) molecule card; and 2) density chart. The
147 molecule card consists of a 2D atomic representation of the
148 candidate and a summary of its properties (Figure 1 (D)). By
149 using this view in parallel with the target protein, users can in-
150 vestigate structural and atomic characteristics and explore po-
151 tential binding regions and orientations. The summary view
152 can be expanded by clicking to show individual property val-
153 ues. By using the predicted properties of molecules, users
154 can comparatively assess the efficacy, safety, and synthesiz-
155 ability of the candidates. In this process, the density chart,
156 built with D3.js, can provide a comprehensive overview of
157 all generated molecules with respect to the metrics of inter-
158 est (Figure 1 (D)). Users can export the information about the
159 generated molecules into various file formats (e.g., json, ex-
160 cel, pdf) for further inspection with third-party tools.

161 2.6 Chatbot Assistant

162 The AI-powered drug discovery takes a long, iterative pro-
163 cess. The users of the system, scientists and AI developers,
164 collaborate to achieve their shared goals of discovering drug
165 candidates, but they may not necessarily have a deep under-
166 standing of each other’s domains. To help users ask ques-
167 tions about biology, chemistry, and biomedical models, we
168 implemented a chatbot assistant. The chatbot built with IBM
169 watsonx Assistant² provides users with natural language re-
170 sponses to users’ queries about technical terms and helpful re-
171 sources to understand more about them as Figure 1 (E) shows.

172 3 Use Case: Chagas Disease

173 This section demonstrates a usage scenario where SPARK
174 can be used to generate and explore small molecule candi-
175 dates for drug discovery. The insights we describe here are
176 speculative resulting from exploratory data analysis, so they
177 need further scientific validation.

²<https://www.ibm.com/products/watsonx-assistant>

Chagas disease is an infectious disease caused by a parasite
found in certain insects. It is a rare disease primarily found
in Central and South America. On the first page, users can
search for target proteins related to Chagas disease. Previous
research has identified that some kinases containing bromod-
omains as a potential drug target [Pezza *et al.*, 2022]. Among
the list, users select a protein target, 5U2E³, from the list.
Once selected, the 3D representation of the protein target is
shown to the users. Users zoom in and pan to explore the
structure in detail.

Moving on to the next page, users choose models and pa-
rameters. Users choose a custom-built biomedical founda-
tion model that was previously implemented on the backend.
Here, users set the number of molecule candidates as 10 to
generate diverse candidates.

On the subsequent page, users set desired properties for
generated molecules through input sliders. Specifically, they
update the drug-likeness and synthetic accessibility score to
be above minimum threshold levels (0.1 and 5, respectively)
so that the generated molecule candidates resemble existing
drugs and are predictably easy to synthesize. Setting the con-
straints on the generated molecules can help bring suitable
drug candidates to the market in a rapid manner.

Finally, the system generates the molecules using the foun-
dation model. As Figure 1 (D) shows, the 10 generated
molecules display diverse structural patterns. By scanning the
predicted properties, one molecule stands out as it appears to
include desired properties, especially with measures of cellu-
lar assays and physical properties less than the correspond-
ing threshold values. Users click on the card to expand the
results. Upon investigation, users realize that the molecule
is predicted to have toxicity through multiple measures as
Figure 1 (E) shows. Users then go back to the previous
step and choose a different model, *PaccMann*^{RL} [Cadow
et al., 2020; Manica *et al.*, 2023], and request to generate 10
molecules with it. The resulting view shows another set of
molecules, which shows another set of interesting molecules.
Users repeat this process iteratively to get a set of interesting
molecules to discuss with other scientists, so they export the
results to PDF and share it with them.

4 Conclusion

In this work, we introduce SPARK, a web-based system that
empowers researchers to harness the power of biomedical
foundation models. By seamlessly integrating AI technolo-
gies with intuitive interfaces, SPARK enables users to guide
model discovery efforts, visualize and interact with results,
and extract valuable scientific insights. This human-centered
interactive AI system can serve as a great example of how col-
laborative intelligence between AI models and human experts
can help accelerate real-world advancements in biomedicine,
particularly in the exciting domain of small molecule drug
candidate generation. Through interactive exploration and it-
erative refinement, SPARK opens doors for biomedical sci-
entists to leverage cutting-edge AI models alongside their sci-
entific knowledge, ultimately leading to more efficient and
potentially groundbreaking discoveries.

³<https://www.rcsb.org/structure/5u2e>

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