IMPROVE: Innovative Methodologies and New Data for Predictive Oncology Model Evaluation



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IMPROVE: Key Challenges & Goal of Partnership

Challenges

Huge Potential: The potential impact of AI on the biomedical community, including in the selection of cancer therapies, cannot be overstated

Underdeveloped: Yet, AI in oncology is still very much a novel and challenging undertaking in need of better *assessment of trustworthiness and reproducibility**

Goal

The Inter-Agency Agreement enables NCI-DOE to jointly *leverage unique capabilities* across the biomedical-computer science spectrum

The two Agencies will help establish stronger connections & **standardized framework** across the data science and clinical research communities

* ~100 papers of TDR models published in the last 4 years all claiming to be "state of the art"

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The IMPROVE Project (phased in FY22)

- Two coupled aims targeting improving AI (deep learning) models for predicting tumor drug response
- Aim 1 Model Curation & Comparison: Development of semi-automatic protocols for comparing deep learning models and identifying attributes that contribute to prediction performance
- Aim 2 Training & Testing: Development of protocols for specifying drug screening experiments and to generate data explicitly aimed at improving model performance





Data Curation **Original paper's data** used to conduct experiments (features, responses, evaluation method)

IMPROVE benchmark data

- Features: pre-computed multiomics and drug features
- Response: single file combining responses from all cell line studies
- Splits: consistent train, validation, and test splits

Framework Development

- Conceptualize standardized
 interface (preprocess, train, infer)
 - Core python modules
- HPO workflow (original paper's data)

- Data loaders
- Parameter parsing modules (CANDLE)
- Refine core modules
- Runtime stats (preprocess, train, infer)
- Identifying edge cases (long preprocess and training) – prep for HPC runs

- Standardized interface implemented
- Cross-study analysis workflow (python)
- Singularity containers
- HPO workflow (benchmark data)

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Model Generalization Analysis: Leveraging DOE supercomputers

Three example models from over 60 models under curation

Models that lead within a single study do not lead in out of study generalization

GraphDRP

	CCLE	CTRP	gCSI	GDSC1	GDSC2
CCLE	0.76	0.50	0.06	0.48	0.05
CTRP	-0.64	0.83	-1.11	-0.15	-0.12
gCSI	-0.01	0.25	0.72	0.25	0.27
GDSC1	-0.15	0.16	-0.39	0.75	0.10
GDSC2	-0.25	0.28	-0.44	0.24	0.79

R² score

Hidra

	CCLE	CTRP	gCSI	GDSC1	GDSC2
CCLE	0.69	0.54	-0.05	0.41	-0.03
CTRP	-0.33	0.82	-0.98	-0.10	-0.01
gCSI	-0.01	0.15	0.62	0.10	0.24
GDSC1	-0.06	0.12	-0.34	0.73	0.09
GDSC2	-0.05	0.24	-0.38	0.14	0.78



DeepTTC

	CCLE	CTRP	gCSI	GDSC1	GDSC2
CCLE	0.73	0.52	0.54	0.61	0.58
CTRP	-0.21	0.78	0.27	0.53	0.54
gCSI	-0.04	0.14	0.68	0.46	0.56
GDSC1	0.05	0.05	0.16	0.71	0.55
GDSC2	0.07	0.26	0.31	0.32	0.76

Brief Bioinform. 2022 Jan; 23(1): bbab356. Published online 2021 Sep 14. doi: <u>10.1093/bib/bbab356</u> PMCID: PMC8769697 PMID: <u>34524425</u>

- "Similar" models trained on the same data show radically different generalizability
- Understanding these behaviors is key to making next generation AI algorithms more robust for clinical application
- Runs on Leadership computing resources are underway in preparation to expand testing of models to include PDO and PDX datasets along with clinical information

Hyperparameter Optimization (HPO) Uncovers Unintended Model Bias (gender bias in this example)

- To study the generality of IMPROVE community models across demographics, we structured a workflow to optimize models based on subsets of the training data
- We built a tool called Cell-GREP to slice the dataset based on metadata in the Cellosaurus encyclopedia, and compare the results of HPO runs on various demographic subsets



• The optimal parameters found by HPO by gender noticeably differ

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• Other studies are underway to understand these effects more broadly

Cell-GREP: https://github.com/ECP-CANDLE/Scratch/tree/master/cell-grep **Demographic aware hyperparameter optimization for cancer** Rylie Weaver, PASC Student Research Competition, 2024 (under review).

IMPROVE's CoderData package: Al readiness for complex pan-cancer datasets



- Launches at AACR'24
- Allows developers to call IMPROVE's curated collection of AI ready data via standard software interface

• **Reduces** data management burden



IMPROVE's Collaboration with NCI Programs: Amplifies Existing Investments

IMPROVE has significant engagement in the community

- Human Cancer Models Initiative (**HCMI**) provides multi-omic cancer molecular data, clinical data and matching organoids
 - Collaborators: Broad/MIT/DFCRC
- PDAC Stromal Reprogramming Consortium (**PSRC**) has committed to providing access to organoids, data and collaborative experiments
 - Collaborators: MD Anderson, UCSD, DFCRC
- Acquired Resistance to Therapy Network (**ARTNet**) ideally suited to help establish clinically-relevant resistance parameters
 - Collaborators: ULCA, UAB, OHSU, OU-CM
- Other NCI funded extramural collaborators
 - Ideker Lab UCSD, Marth Lab UoU/SLC, Chiu Lab UPitt



Generation of "nearer to patient" Datasets to Improve Models

- Gathering initial datasets for image-based response measures and assess how the models will need to adapt to data generated from PDO
 - The drugs being tested cover most of the MoAs needed for a pancancer study and a selection of common bystander drugs.
- Concurrently IMPROVE is running studies with labs that have significant data sets for other cancer types to create a link between IMPROVE's data and community data
 - UCLA, MD Anderson/DFCRC/UCSD, and UChicago
- IMPROVE will expand data generation focusing on pancreatic adenocarcinoma, GBM, AML and sarcoma, against an expanded repertoire of drugs
 - Combination therapies are also being considered

Search By Model Name													
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IMPROVE is an Open Community

- Collaborative Core Modeling Groups (CCMG)
 - Mayo Clinic (Chen Wang)
 - Texas Tech University (Ranadip Pal)
 - Pacific Northwest National Laboratory (Sara Gosline)
- Events have been held at: ANL, U of Utah Salt Lake, UCSD and U Pitt (virtual)
- The next Hackathon is in Boston May 2024
 - Theme is data readiness for AI
 - Focused discussions on: Data collection, curation, and benchmark dataset preparation





CCMG Kickoff Jan'23

The IMPROVE Framework: All Resources Available to the Public

- A GitHub project (<u>https://github.com/JDACS4C-IMPROVE</u>), including repositories:
 - Drug response prediction models
 - Model evaluation workflows and APIs
 - Other relevant resources, e.g. data preprocessing scripts and documentation
 - Tutorial for making models compliant with the IMPROVE framework
 - Introduction and guidelines for curating models
- Data & curated models used by IMPROVE framework in MODAC (<u>https://modac.cancer.gov/</u>)
- Project website: (https://datascience.cancer.gov/collaborations/nci-departmentenergy-collaborations/improve)

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Discussion

