INFOMEDEX

PRECISION GENETICS

Recap On InfoMedEx

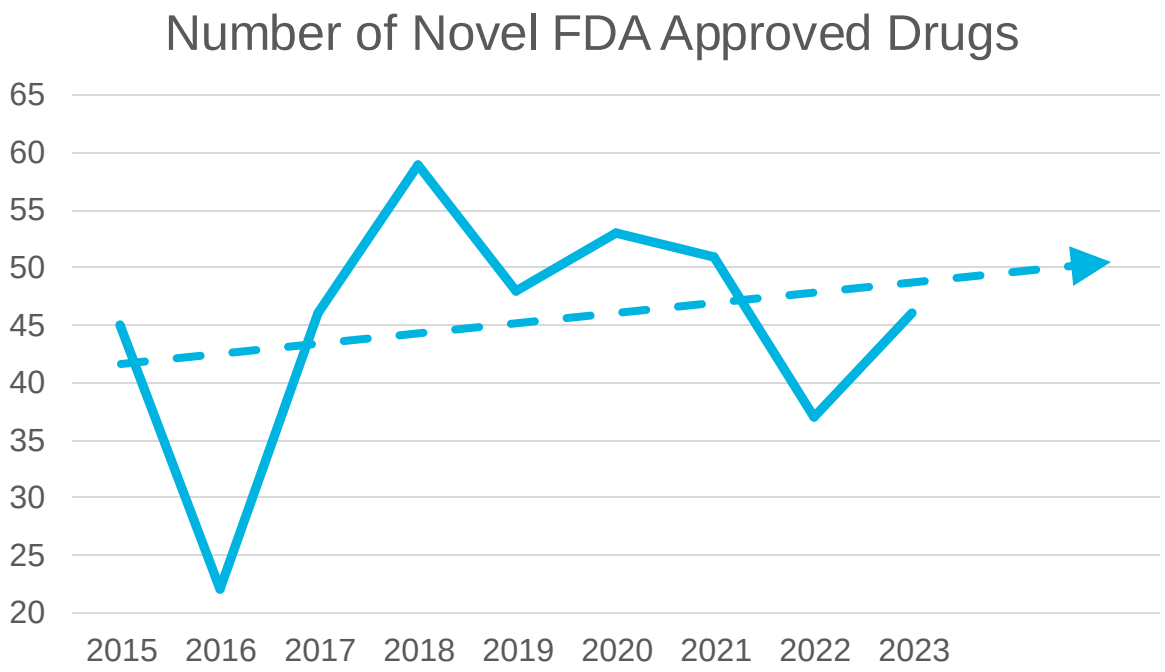
What is InfoMedEx?

AI models to predict drug-drug interactions

- Deep learning models
- Given two drug (e.g. Aspirin and Warfarin) predict the interaction for reports or be provided by an API to other companies
  - Aspirin may increase the anticoagulant activities of Warfarin.

Why Develop InfoMedEx?

- Allows us to quickly add new drugs to our reports; onboard new assays
- Applications in drug development
- Develop IP and display technical expertise to investors



PRECISION GENETICS

Interactions between your drugs

Moderate

aprepitant ⇄ cariprazine

Applies to: aprepitant, cariprazine

MONITOR: Coadministration with moderate inhibitors of CYP450 3A4 may increase the plasma concentrations of cariprazine and its major active metabolite, didesmethyl cariprazine (DDCAR), both of which are primarily metabolized by the isoenzyme. When cariprazine (0.5 mg/day) was coadministered with the potent CYP450 3A4 inhibitor, ketoconazole (400 mg/day), cariprazine peak plasma concentration (Cmax) and systemic exposure (AUC) increased by approximately 3.5- and 4-fold, respectively, while Cmax and AUC of DDCAR increased by approximately 1.5-fold each. The Cmax and AUC of another active metabolite, desmethyl cariprazine (DCAR), decreased by approximately one-third. The extent to which other, less potent inhibitors of CYP450 3A4 may interact with cariprazine and its metabolites is unknown.

MANAGEMENT: Caution is advised when cariprazine is prescribed with moderate CYP450 3A4 inhibitors. Patients should be monitored for adverse effects such as extrapyramidal symptoms, cognitive and motor impairment, hyperglycemia, dyslipidemia, weight gain, orthostatic hypotension, leukopenia, neutropenia, seizures and dysphagia, and the dosage of cariprazine adjusted as necessary in accordance with the product labeling.

References

1. "Product Information. Vraylar (cariprazine)." Actavis Pharma, Inc. (2015):

HIGHLIGHTS OF PRESCRIBING INFORMATION

These highlights do not include all the information needed to use VRAYLAR safely and effectively. See full prescribing information for VRAYLAR.

VRAYLAR™ (cariprazine) capsules, for oral use
Initial U.S. Approval: XXXX

WARNING: INCREASED MORTALITY IN ELDERLY PATIENTS WITH DEMENTIA-RELATED PSYCHOSIS

See full prescribing information for complete boxed warning.

- **Elderly patients with dementia-related psychosis treated with antipsychotic drugs are at an increased risk of death.**
- **VRAYLAR is not approved for the treatment of patients with dementia-related psychosis. (5.1)**

----------INDICATIONS AND USAGE----------

VRAYLAR is an atypical antipsychotic indicated for the:

- Treatment of schizophrenia (1)
- Acute treatment of manic or mixed episodes associated with bipolar I disorder (1)

----------DOSAGE AND ADMINISTRATION----------

- Administer VRAYLAR once daily with or without food (2)

	Starting Dose	Recommended Dose
Schizophrenia (2.2)	1.5 mg/day	1.5 mg to 6 mg/day
Bipolar Mania (2.3)	1.5 mg/day	3 mg to 6 mg/day

- Doses above 6 mg daily do not confer significant benefit but increased the risk of dose-related adverse reactions.

----------DOSAGE FORMS AND STRENGTHS----------

Capsules: 1.5 mg, 3 mg, 4.5 mg, and 6 mg (3)

----------CONTRAINDICATIONS----------

Known hypersensitivity to VRAYLAR (4)

----------WARNINGS AND PRECAUTIONS----------

- *Cerebrovascular Adverse Reactions in Elderly Patients with Dementia-Related Psychosis:* Increased incidence of cerebrovascular adverse reactions (e.g., stroke, transient ischemic attack) (5.2)
- *Neuroleptic Malignant Syndrome:* Manage with immediate discontinuation and close monitoring (5.3)
- *Tardive Dyskinesia*: Discontinue if appropriate (5.4)
- *Late-Occurring Adverse Reactions:* Because of VRAYLAR's long half-life, monitor for adverse reactions and patient response for several weeks after starting VRAYLAR and with each dosage change (5.5)
- *Metabolic Changes*: Monitor for hyperglycemia/diabetes mellitus, dyslipidemia and weight gain (5.6)
- *Orthostatic Hypotension*: Monitor heart rate and blood pressure and warn patients with known cardiovascular or cerebrovascular disease, and risk of dehydration or syncope (5.8)

----------ADVERSE REACTIONS----------

Most common adverse reactions (incidence ≥ 5% and at least twice the rate of placebo) were (6.1):

- Schizophrenia: extrapyramidal symptoms and akathisia
- Bipolar mania: extrapyramidal symptoms, akathisia, dyspepsia, vomiting, somnolence, and restlessness

To report SUSPECTED ADVERSE REACTIONS, contact Actavis at 1-800-272-5525 or FDA at 1-800-FDA-1088 or www.fda.gov/medwatch.

----------DRUG INTERACTIONS----------

- Strong CYP3A4 inhibitors: reduce VRAYLAR dosage by half (2.4, 7.1)
- CYP3A4 inducers: do not recommend use with VRAYLAR (2.4, 7.1)

----------USE IN SPECIFIC POPULATIONS----------

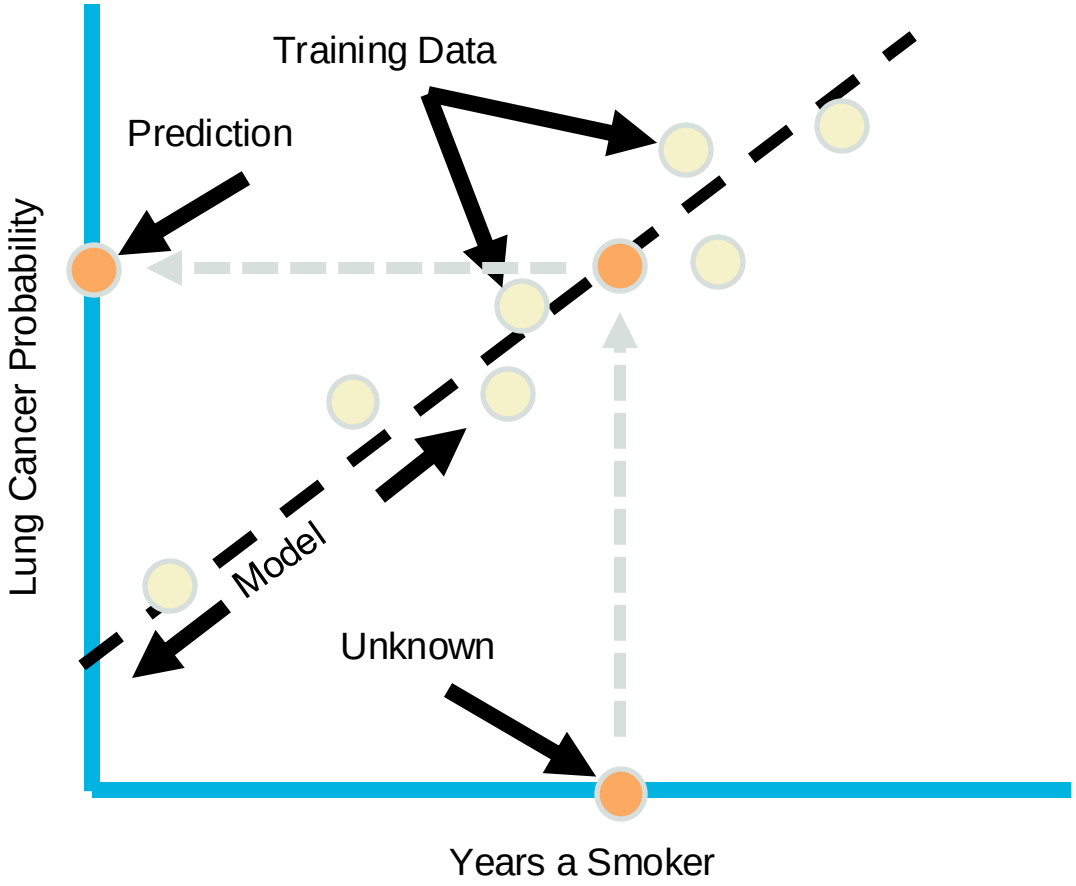
- *Pregnancy:* May cause extrapyramidal and/or withdrawal symptoms in neonates with third trimester exposure (8.1)

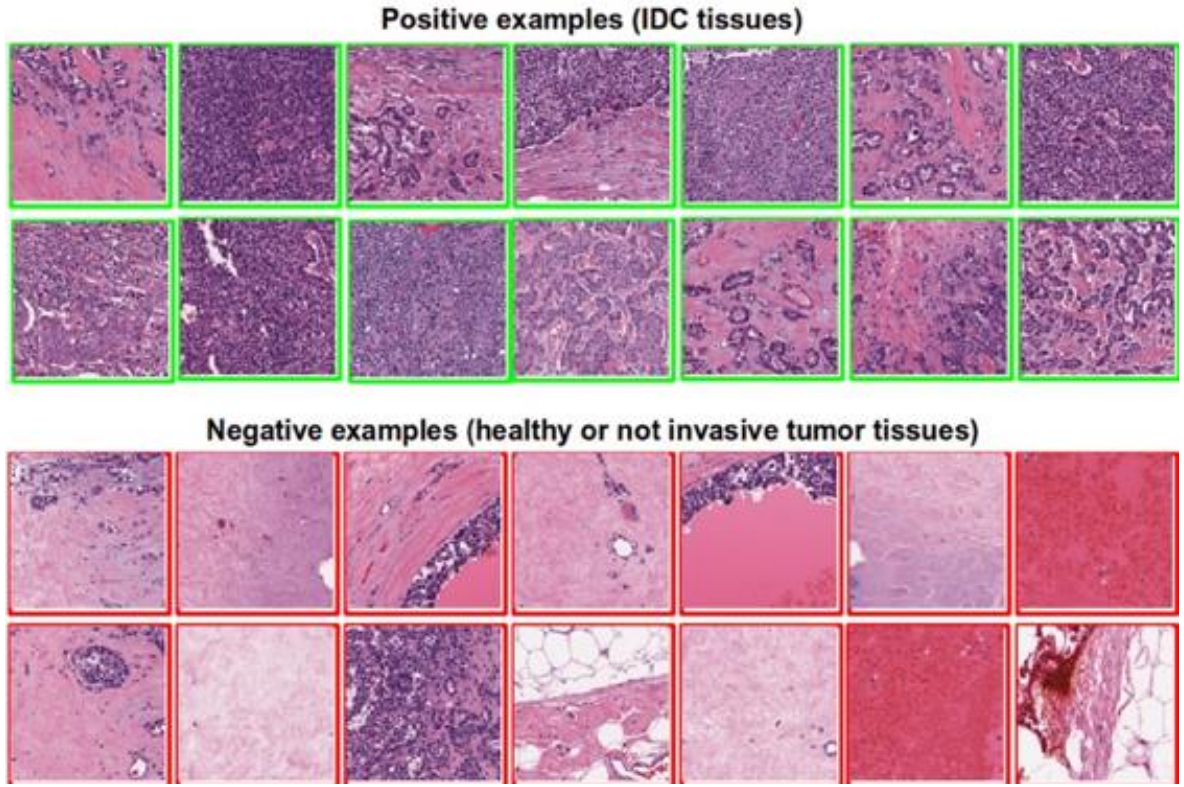
See 17 for PATIENT COUNSELING INFORMATION

Revised: 09/2015

FULL PRESCRIBING INFORMATION: CONTENTS*

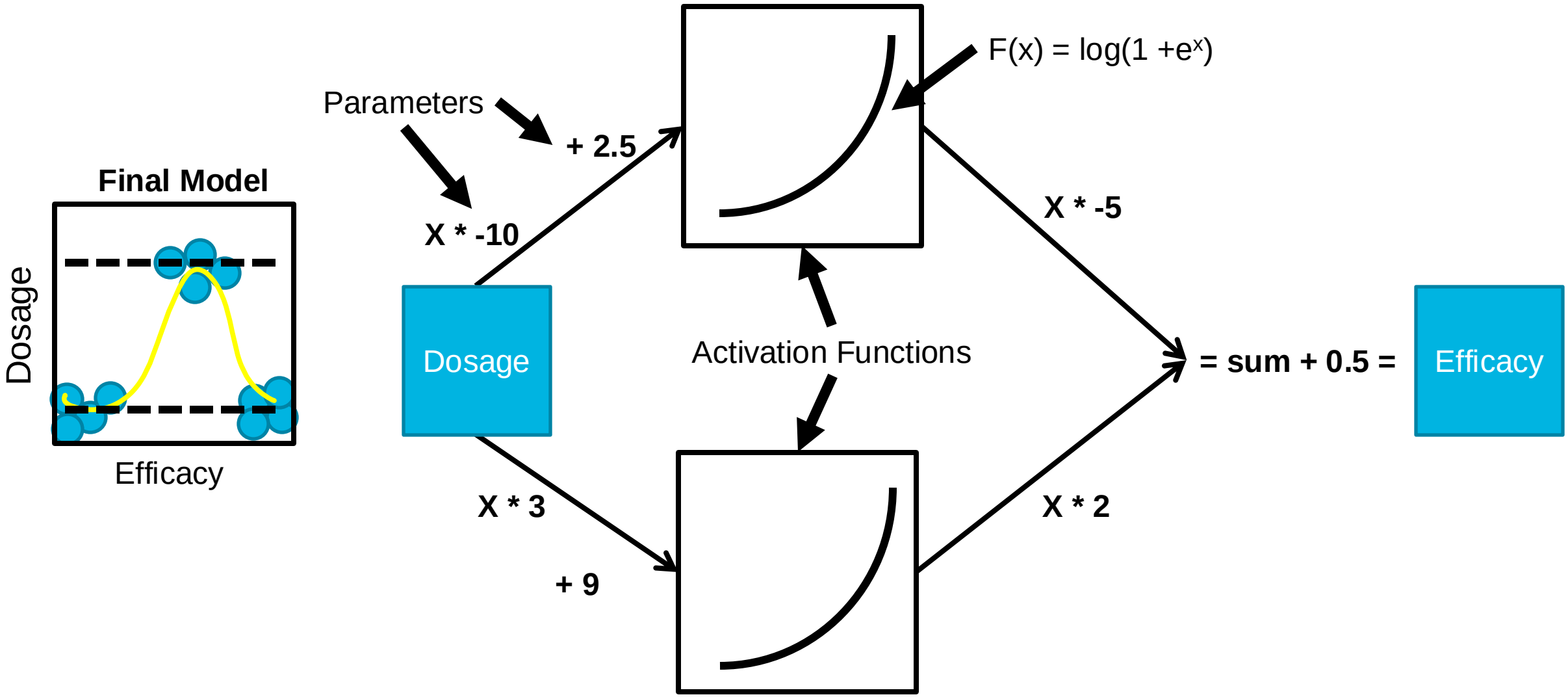
Modeling, Data, Learning



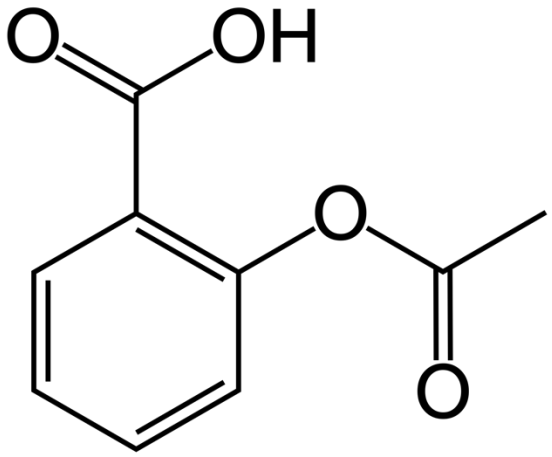


PRECISION GENETICS

Simple Neural Network



Drug Chemical Structure (SMILES)

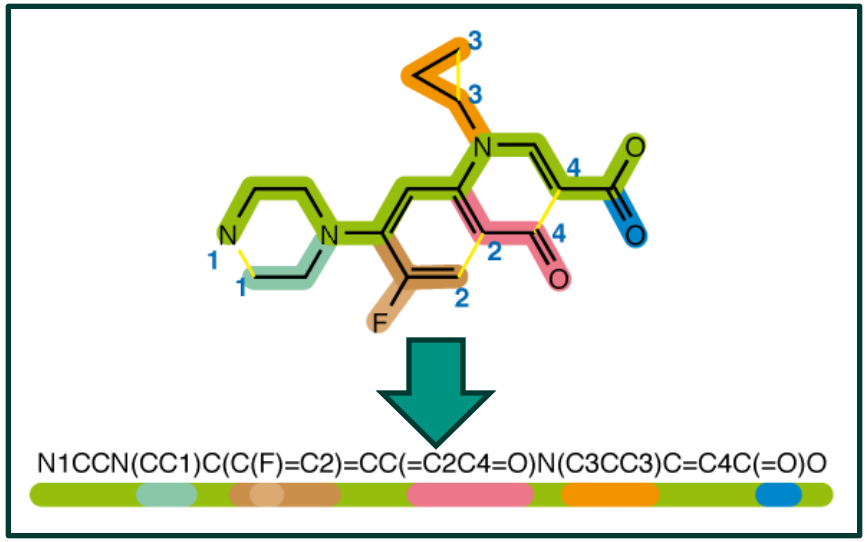


CC(=O)OC1=CC=CC=C1C(=O)O

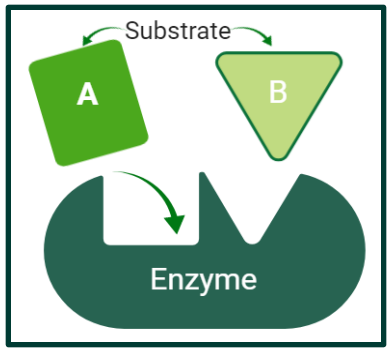
[CH3;!R;C], [C;!R;COO], (, =, [O;!R;C],), [O;!R;CC], [c;R;CCO], 1, [cH;R;CC], [cH;R;CC], [cH;R;CC], [cH;R;CC], [c;R;CCC], 1, [C;!R;COO], (, =, [O;!R;C],), [OH;!R;C]

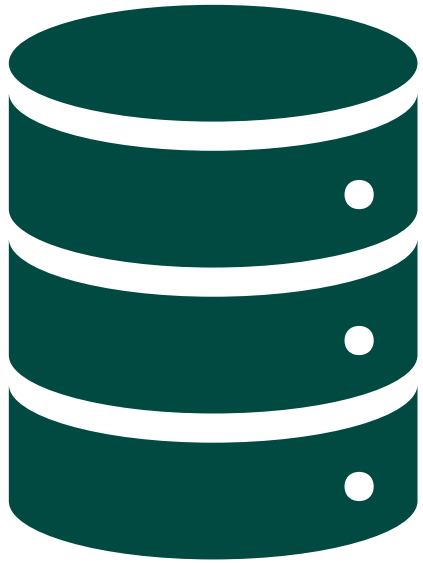
ML Transformers

- Chemical structure has its order maintained through a transformer
- Can be trained to emphasize important features of a sentence



Acetylsalicylic acid may increase the anticoagulant activities of **Streptokinase**.
Or
Minor/Moderate/Major





DDI Database

PxNav

DRUGBANK

PubChem

TTD

snu-lcbc/**atom-in-SMILES**

Atom-in-SMILES tokenizer for SMILES strings.

2 Contributors | 0 Issues | 22 Stars | 0 Forks

Drugs.com
Know more. Be sure.

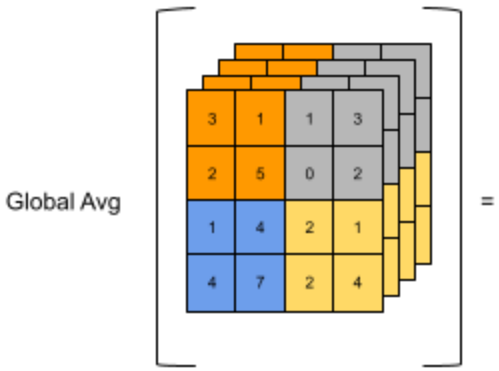
PRECISION GENETICS

InfoMedEx Model Update

PRECISION GENETICS

Interaction Type Prediction Model

- More accurate, with clear room for improvement
- Includes drugs and interaction types that occur at least 50 times
  - Improved from 100; more types of interactions predicted >160
- Focal Loss
  - Handles class imbalance better, a major challenge we were encountering before
- Adding a dedicated decoder for the transformer encoder
- Trained using 198gb of ram, 48 CPUs, 4 GPUs over 150 hours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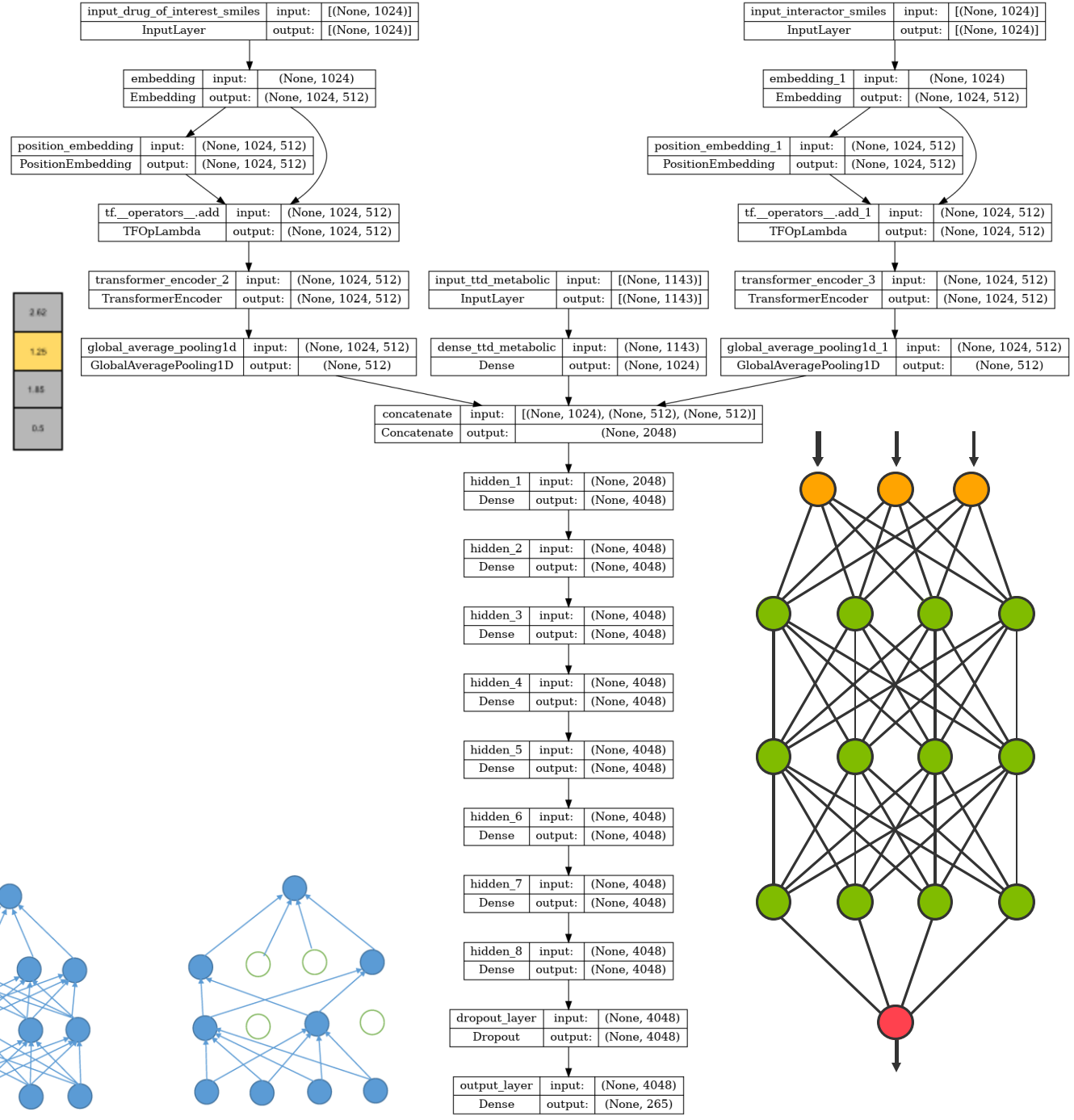
2 5 0 2
1 4 2 1
4 7 2 4
2.62
1.25
1.85
0.5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InputLayer | output: | [(None, 1024)]
embedding | input: | (None, 1024)
Embedding | output: | (None, 1024, 512)
position_embedding | input: | (None, 1024, 512)
PositionEmbedding | output: | (None, 1024, 512)
tf.__operators__.add | input: | (None, 1024, 512)
TFOpLambda | output: | (None, 1024, 512)
transformer_encoder_2 | input: | (None, 1024, 512)
TransformerEncoder | output: | (None, 1024, 512)
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InputLayer | output: | [(None, 1024)]
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PositionEmbedding | output: | (None, 1024, 512)
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hidden_2 | input: | (None, 4048)
Dense | output: | (None, 4048)
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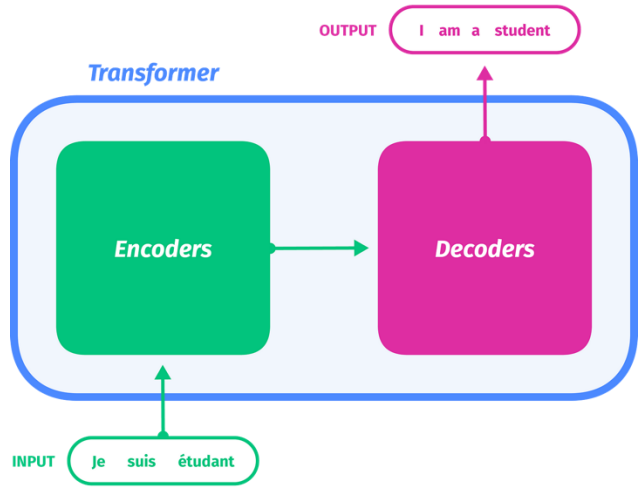
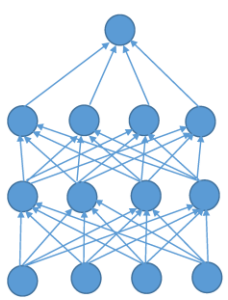
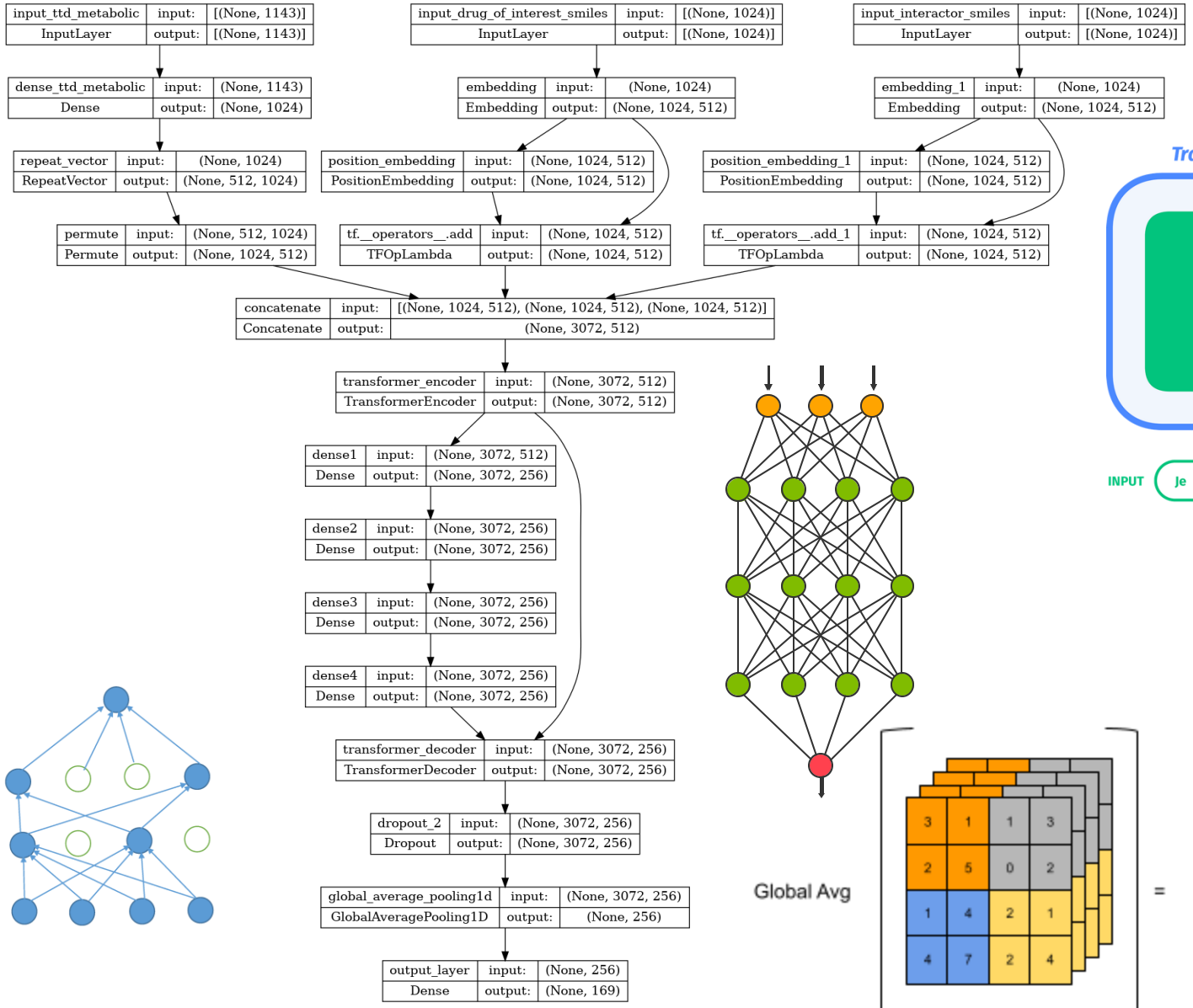
Dense | output: | (None, 4048)
hidden_4 | input: | (None, 4048)
Dense | output: | (None, 4048)
hidden_5 | input: | (None, 4048)
Dense | output: | (None, 4048)
hidden_6 | input: | (None, 4048)
Dense | output: | (None, 4048)
hidden_7 | input: | (None, 4048)
Dense | output: | (None, 4048)
hidden_8 | input: | (None, 4048)
Dense | output: | (None, 4048)
dropout_layer | input: | (None, 4048)
Dropout | output: | (None, 4048)
output_layer | input: | (None, 4048)
Dense | output: | (None, 265)


OUTPUT
I am a student
Transformer
Encoders
Decoders
INPUT
Je suis étudant




input_ttd_metabolic | input: | [(None, 1143)]
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InputLayer | output: | [(None, 1024)]
input_interactor_smiles | input: | [(None, 1024)]
InputLayer | output: | [(None, 1024)]
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Dense | output: | (None, 1024)
embedding | input: | (None, 1024)
Embedding | output: | (None, 1024, 512)
embedding_1 | input: | (None, 1024)
Embedding | output: | (None, 1024, 512)
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RepeatVector | output: | (None, 512, 1024)
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PositionEmbedding | output: | (None, 1024, 512)
position_embedding_1 | input: | (None, 1024, 512)
PositionEmbedding | output: | (None, 1024, 512)
permute | input: | (None, 512, 1024)
Permute | output: | (None, 1024, 512)
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TFOpLambda | output: | (None, 1024, 512)
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TFOpLambda | output: | (None, 1024, 512)
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TransformerEncoder | output: | (None, 3072, 512)
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Dense | output: | (None, 3072, 256)
dense2 | input: | (None, 3072, 256)
Dense | output: | (None, 3072, 256)
dense3 | input: | (None, 3072, 256)
Dense | output: | (None, 3072, 256)
dense4 | input: | (None, 3072, 256)
Dense | output: | (None, 3072, 256)
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TransformerDecoder | output: | (None, 3072, 256)
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Dropout | output: | (None, 3072, 256)
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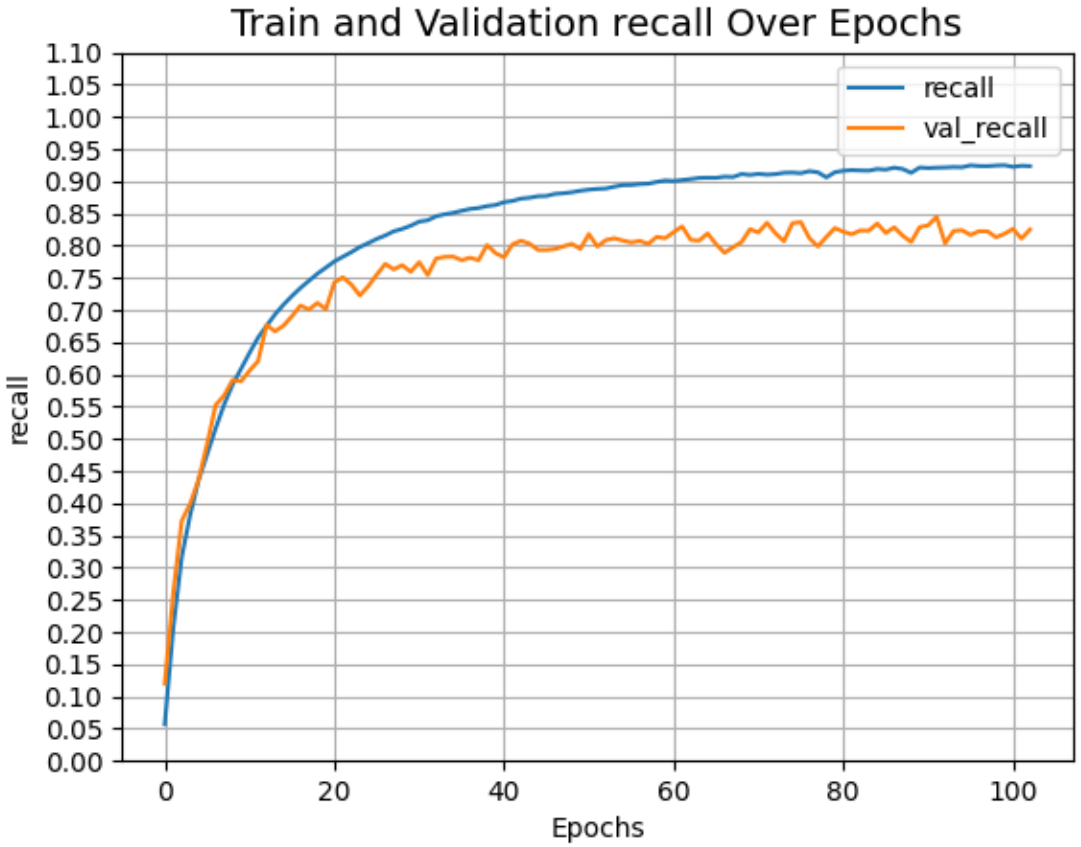
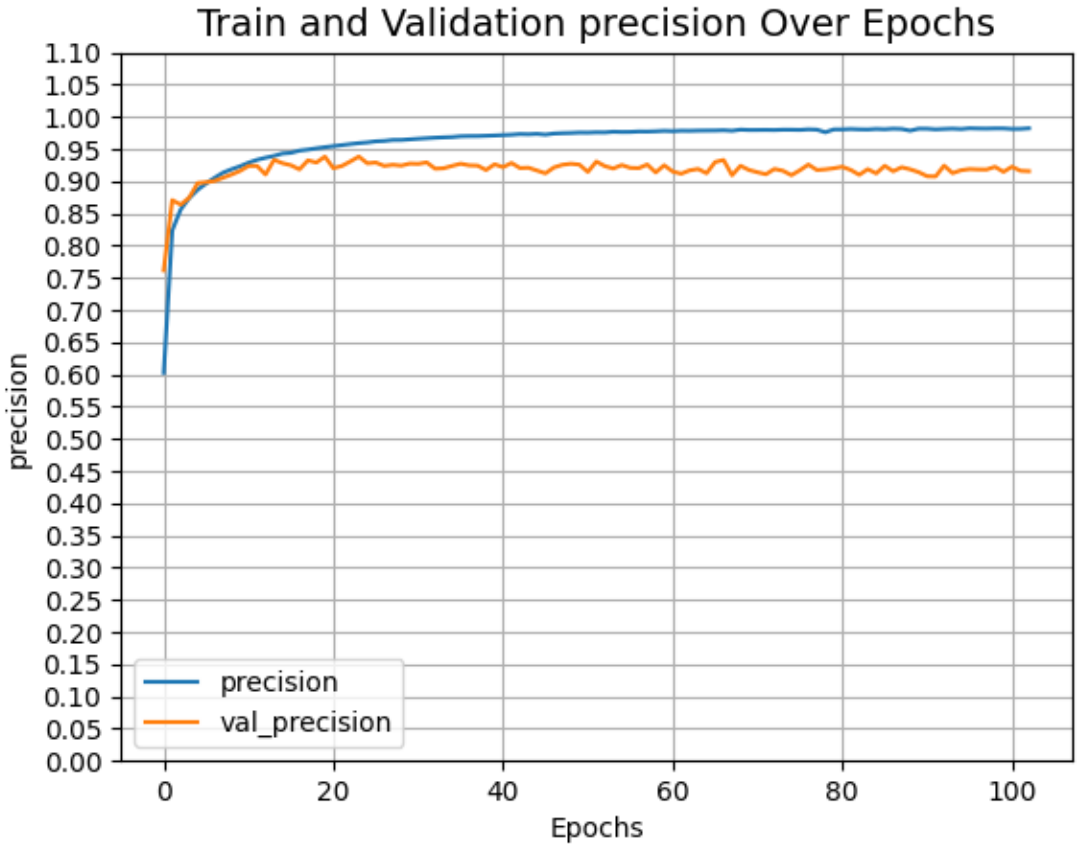
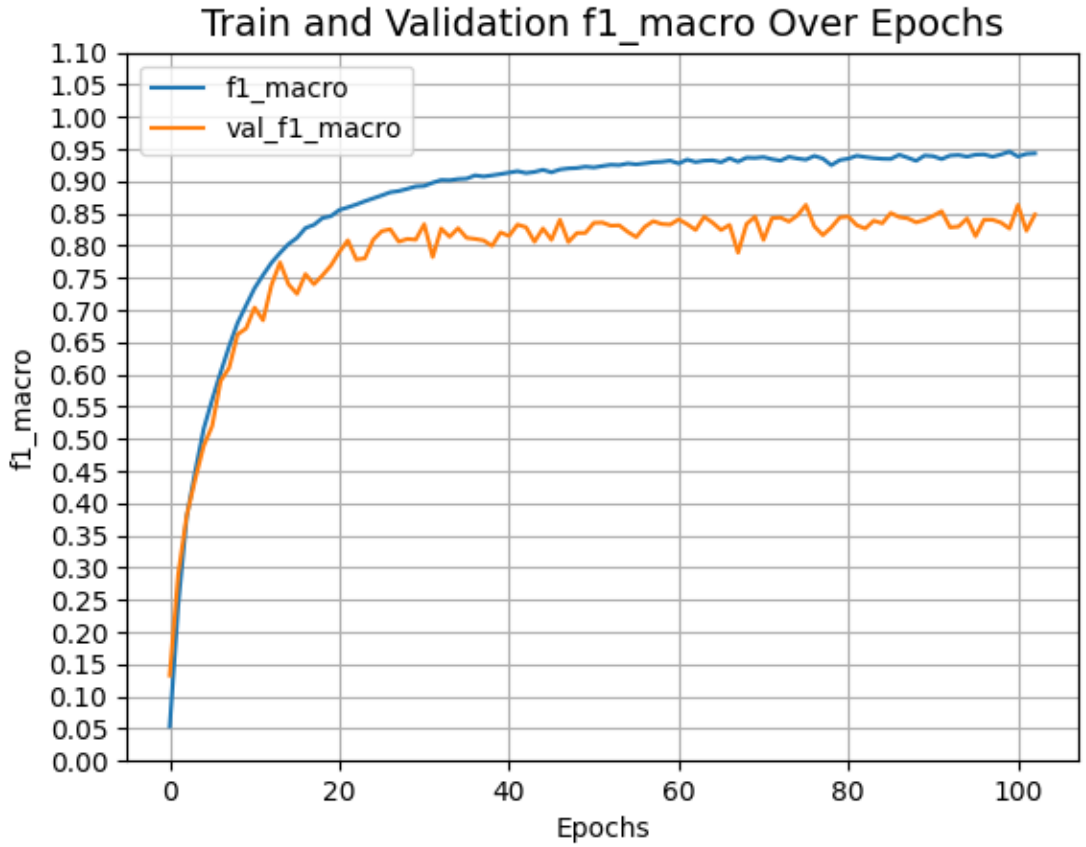
GlobalAveragePooling1D | output: | (None, 256)
output_layer | input: | (None, 256)
Dense | output: | (None, 169)
OUTPUT
I am a student
Transformer
Encoders
Decoders
INPUT
Je suis étudant
Global Avg
=





PRECISION GENETICS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val_f1_macro
f1_macro
Epochs
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1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
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0.05
0.00
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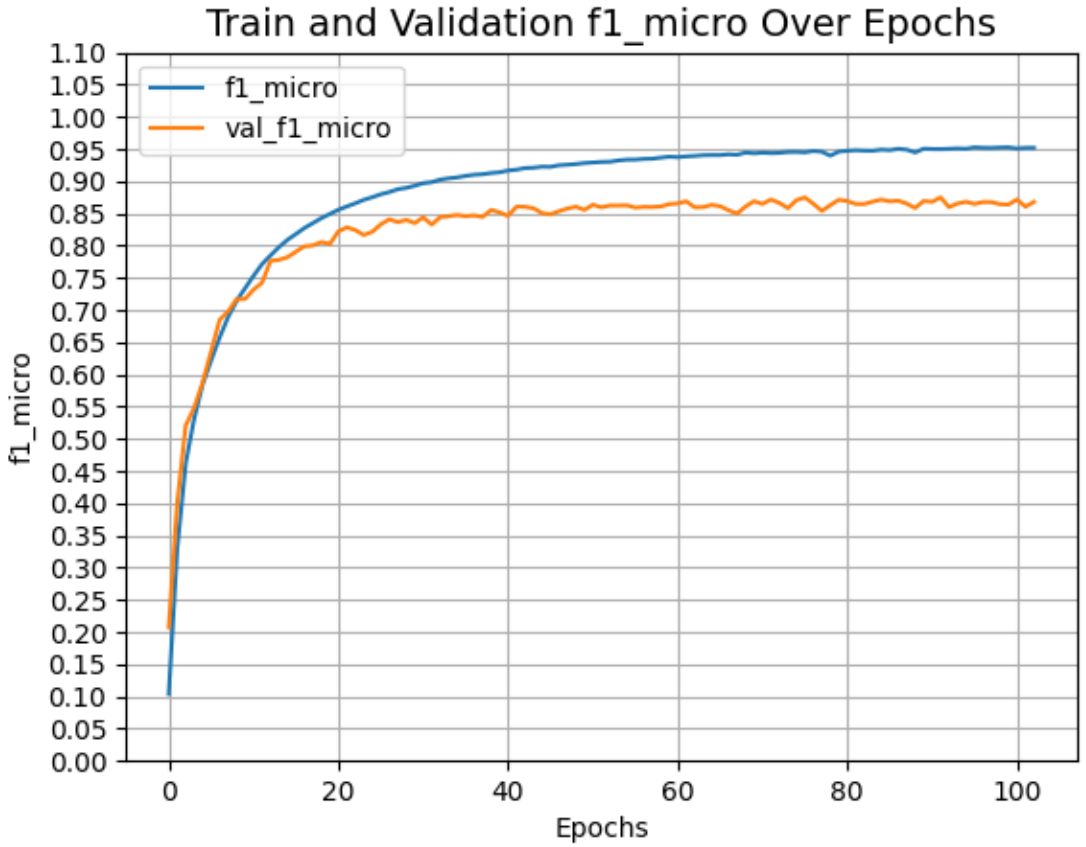
20
40
60
80
100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val_f1_micro
f1_micro
Epochs
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1.05
1.00
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0.90
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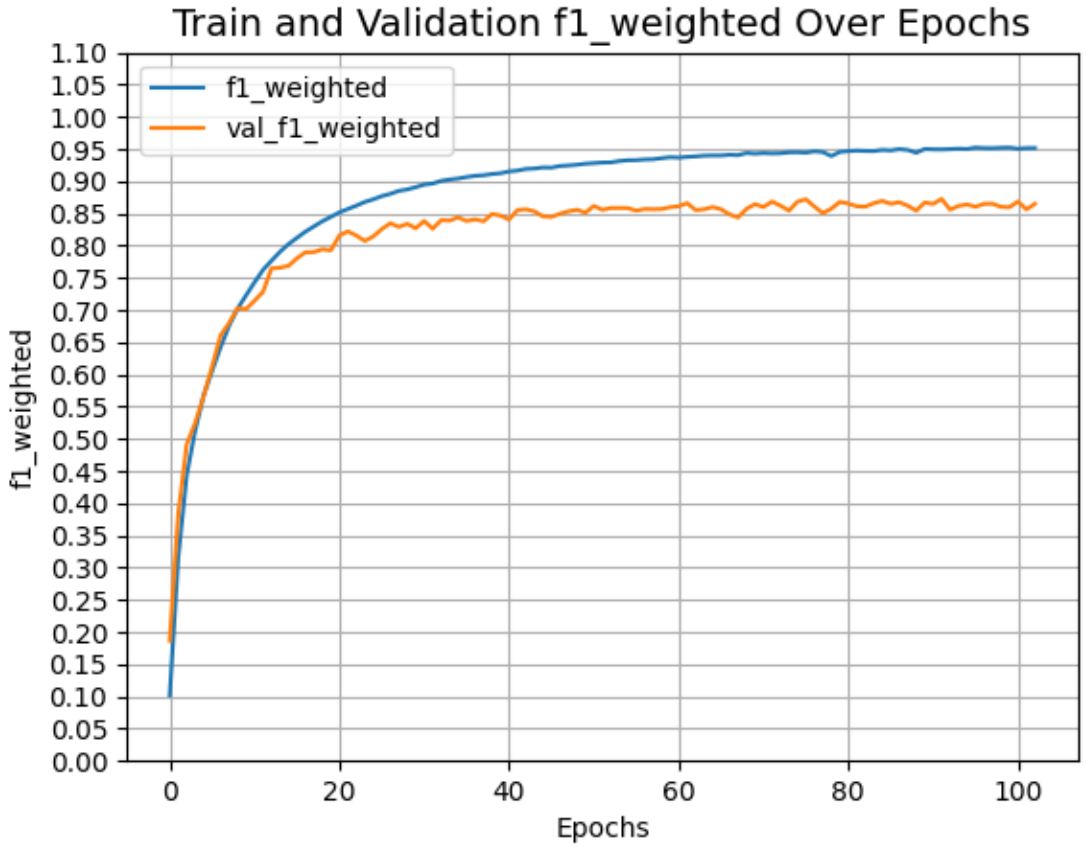
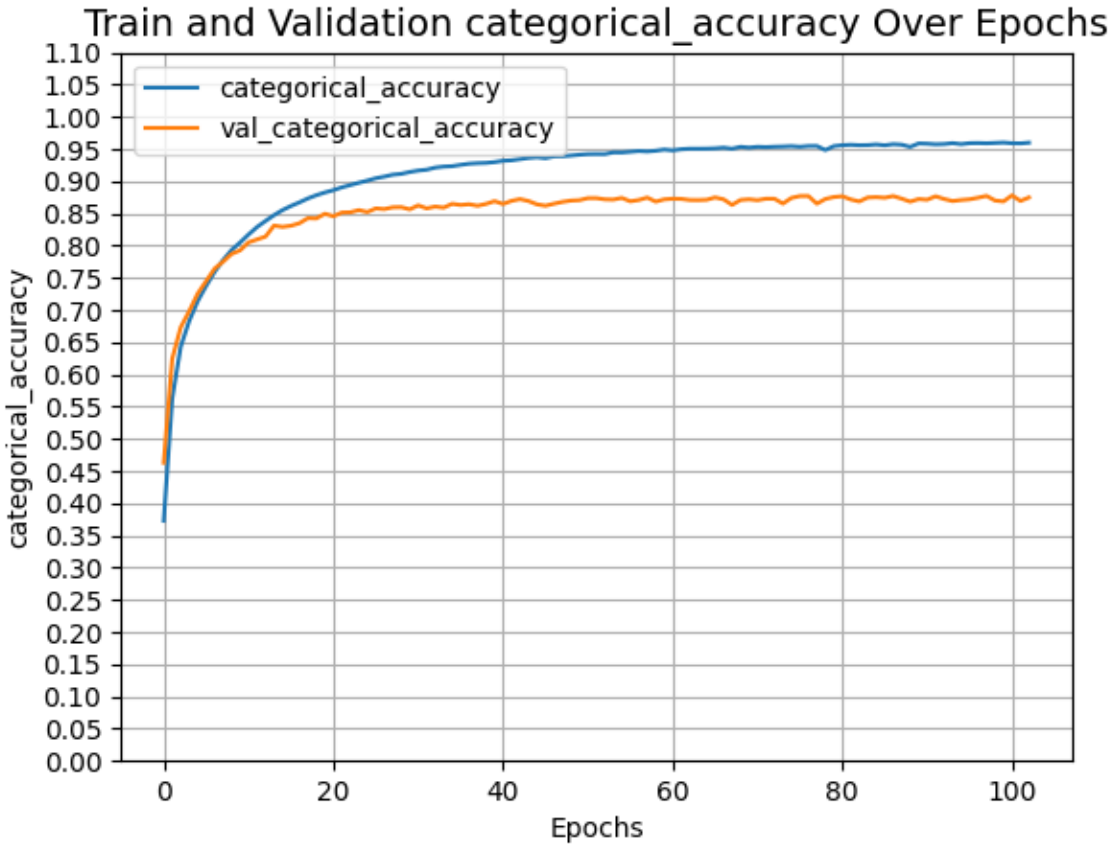




PRECISION GENETICS

InfoMedEx Databases

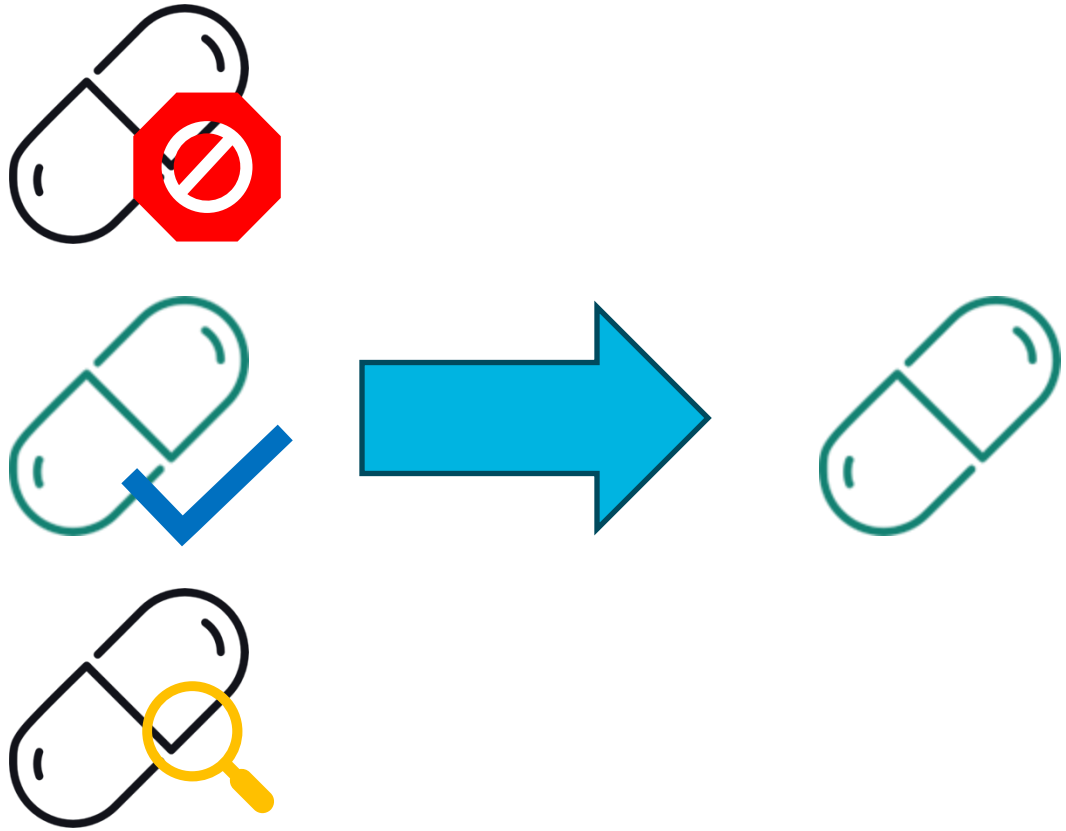
PRECISION GENETICS

Drug Alternatives Database

PRECISION GENETICS

Recommending Drug Alternatives

- Database of drugs organized by condition treated, drug type, etc.
  - Antimanic Agents, Antineoplastic Topoisomerase Inhibitors
- If a drug combination has adverse interactions, we can offer an alternative without an interaction from the same class



PRECISION GENETICS

Drug Alternatives Database

- Pulled from RxList
- 3,605 drugs
- 738 Categories

RxList
The Internet Drug Index

Condition	Drug
Anxiolytics, Benzodiazepines	Seizalam
Anxiolytics, Benzodiazepines	Tranxene
Anxiolytics, Benzodiazepines	Valium
Anxiolytics, Benzodiazepines	Xanax XR
Anxiolytics, Nonbenzodiazepines	Buspirone
Anxiolytics, Nonbenzodiazepines	dopamine
Anxiolytics, Nonbenzodiazepines	Meprobamate
Anxiolytics, Nonbenzodiazepines	granulocytes
Appetite Stimulants	oxandrolone
Appetite Stimulants	dronabinol
Appetite Stimulants	Megace ES
Appetite Stimulants	Oxandrin
Appetite Stimulants	Marinol
Appetite Stimulants	mirtazapine
Appetite Stimulants	Remeron
Appetite Stimulants	cyproheptadine
augmentin antimicrobial for infections	Amoxicillin
augmentin antimicrobial for infections	Augmentin
B Vitamins	thiamine
B Vitamins	niacin
B Vitamins	pantothenic acid
B Vitamins	biotin

DDI References Database

PRECISION GENETICS

DDI References Web Scraper

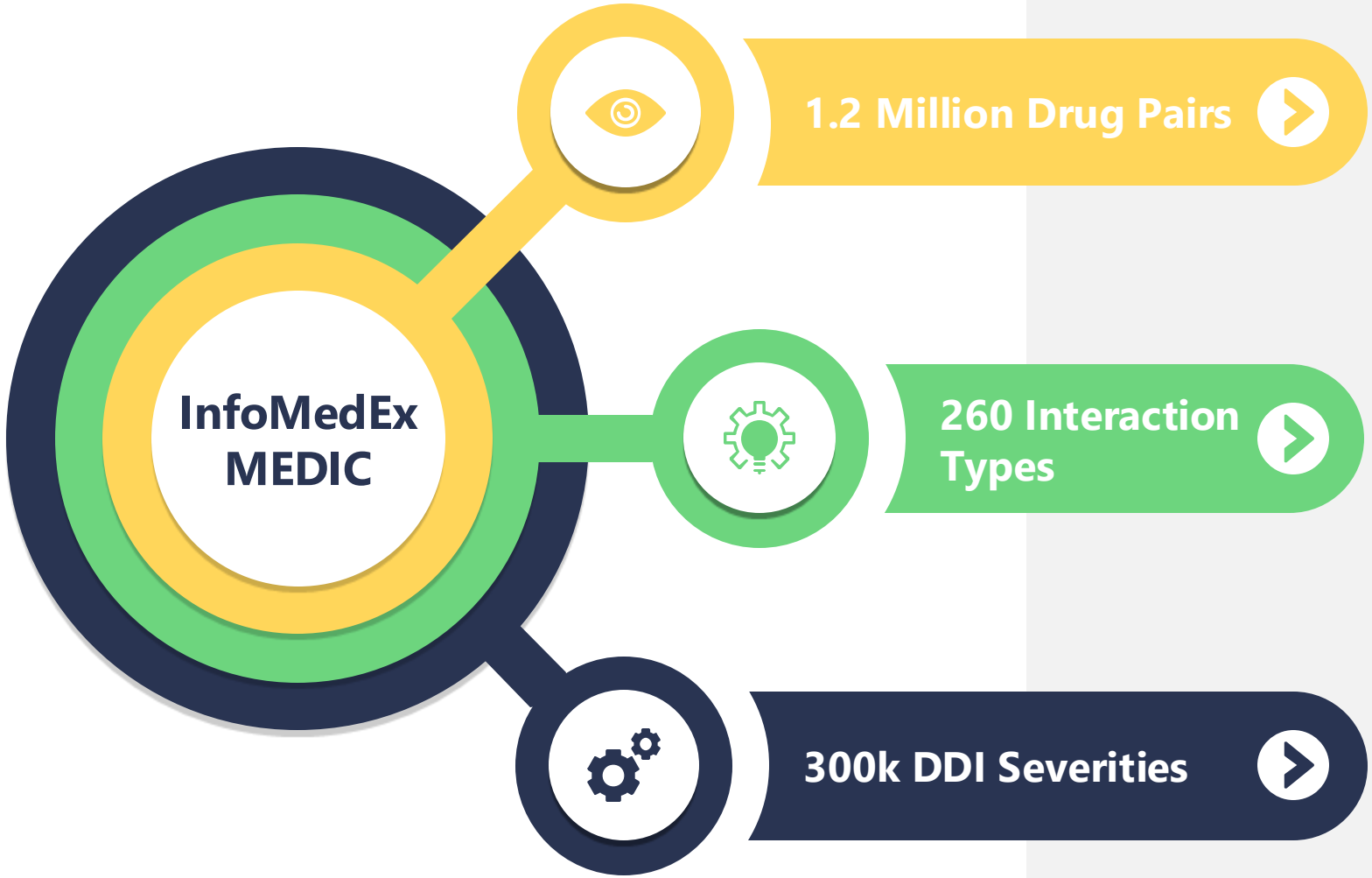
- Code pulls from Google Scholar the 3 most prominent references for a DDI
- Example for Levothyroxine and Ritonavir:
  - Title: Probable interaction between levothyroxine and ritonavir: Case report and literature review
  - Authors: R Sahajpal, RA Ahmed, CA Hughes American Journal of, 2012 - academic.oup.com
  - URL: https://academic.oup.com/ajhp/article-abstract/74/8/587/5103380

InfoMedEx MEDIC Database

Medical Drug Interaction Compendium

PRECISION GENETICS

Key Points



Including Information on chemical structure, metabolic targets, interaction types

For each pair there is an interaction type. For example: risk of hypertension, nephrotoxicity, or death

This includes information on contraindicated, major, moderate, and minor interactions

Elements In The MEDIC Database

- Drug Of Interest & Interactor
- Interaction Severity Level Number
- Interaction Severity Level Letter
- Severity Based Warning
- DDI Interaction
- DDI Interaction Effect Warning
- DDI References

INFOMEDEX

PRECISION GENETICS

Severity Warnings

- **A**: No Interaction. (Not displayed on DDI reports)
- **B**: Coadministration of Drug 1 and Drug 2 has a low risk of adverse effects in some patients. Consider alternative medications if these effects are unacceptable to the patient.
- **C**: Coadministration of Drug 1 and Drug 2 has a moderate risk of adverse effects in some patients. Monitor the patient for potential adverse effects and dosage adjustments may be needed.
- **D**: Coadministration of Drug 1 and Drug 2 has an elevated risk of adverse side effects in some patients. Consider alternative medications or treatment options. If the benefits outweigh the risks steps should be taken to minimize the risks such as close monitoring or empirical dosage adjustments.
- **X**: Coadministration of Drug 1 and Drug 2 is contraindicated due to the potential for severe health risks. Find alternative medication or treatment options.

Interaction Warnings Language Example

- **Interaction**
  - Drug 1 can cause a decrease in the absorption of Drug 2 resulting in a reduced serum concentration and potentially a decrease in efficacy.

- **Warning**
  - If Drug 1 and Drug 2 are given concomitantly monitor patient for decreased Drug 2 efficacy and adjust dosage according to the drug label or discontinue based on patient response.

Example Implementation Of MEDIC

PRECISION GENETICS

PRECISION GENETICS

Precision Genetics

430 Roper Mountain Rd Greenville, SC 29615

PATIENT INFORMATION		SPECIMEN DETAILS		PROVIDER INFORMATION	
NAME:	PGXA PGXA-02	SAMPLE ID:	PGXA-02	PROVIDER:	
DOB:	01/01/2024	SPECIMEN TYPE:	buccal Swab	FACILITY:	
SEX:		COLLECTION DATE:	01/26/2024		
		RECEIVED DATE:	01/26/2024		
		REPORT DATE:	02/13/2024		

PGx Primary

Current Medication	Selected Medication	Interaction Severity	Interaction	InfoMedEx
Warfarin	Aspirin		Bleeding Risk	
Amlodipine	Aspirin		Hypertension Risk	

Unrecognized Medications: None

Defined as medications that are not included in the testing database, medications that were misspelled on the Sonic PGx request form, medications that were listed as drug classes instead of individual medications, and/or medications not available in Australia. Some medications use US spelling.

Outside of Scope Medications: None

Defined as those that do not have PGx currently have pharmacogenetic guidance available to report.

PRECISION GENETICS

Precision Genetics
430 Roper Mountain Rd Greenville, SC 29615

NAME:	PGXA PGXA-02	SAMPLE ID:	PGXA-02	PROVIDER:	
DOB:	01/01/2024	SPECIMEN TYPE:	buccal Swab	FACILITY:	
SEX:		COLLECTION DATE:	01/26/2024		
		RECEIVED DATE:	01/26/2024		
		REPORT DATE:	02/13/2024		

PGx Primary

Medication		Interaction Risk Level	Interaction
Current	Aliskiren	 **Contraindicated (X)**	• Coadministration of Aliskiren and Lisinopril is contraindicated due to the potential for severe health risks. Find alternative medication or treatment options. • The risk or severity of hypotension hyperkalemia and nephrotoxicity can be increased when Lisinopril is combined with Aliskiren. • If Aliskiren and Lisinopril are used concomitantly monitor patient for excessive tiredness and fatigue, lightheadedness, syncope, chest pain, heart palpitations, muscle weakness, decreased urination, swelling from fluid retention and high blood pressure.
Selected	Lisinopril		

References:

- Aliskiren FDA Label Information
- Lisinopril FDA Label Information
- Daugherty, K. K. (2008). Aliskiren. *American Journal of Health-System Pharmacy*, *65*(14), 1323-1332.
- Sanoski, C. A. (2009). Aliskiren: an oral direct renin inhibitor for the treatment of hypertension. *Pharmacotherapy: The Journal of Human Pharmacology and Drug Therapy*, *29*(2), 193-212.
- Pool, J. L. (2007). Direct renin inhibition: focus on aliskiren. *Journal of Managed Care Pharmacy*, *13*(8 Supp B), 21-33.

PRECISION GENETICS

Precision Genetics
430 Roper Mountain Rd Greenville, SC 29615

NAME:	PGXA PGXA-02	SAMPLE ID:	PGXA-02	PROVIDER:	
DOB:	01/01/2024	SPECIMEN TYPE:	buccal Swab	FACILITY:	
SEX:		COLLECTION DATE:	01/26/2024		
		RECEIVED DATE:	01/26/2024		
		REPORT DATE:	02/13/2024		

PGx Primary

Medication		Interaction Risk Level	Interaction
Current	Ziprasidone	 **Moderate (C)**	• Coadministration of Ziprasidone and Lisinopril has a moderate risk of adverse effects in some patients. Monitor the patient for potential adverse effects and dosage adjustments may be needed. • Ziprasidone may increase the antihypertensive activities of Lisinopril. • If Ziprasidone and Lisinopril are given concomitantly monitor patient for decreased blood pressure and blurry vision, confusion, syncope, dizziness, or trouble concentrating.
Selected	Lisinopril		

References:
- Ziprasidone FDA Label Information
- Lisinopril FDA Label Information
- Buzea, C. A., Dima, L., Correll, C. U., & Manu, P. (2022). Drug–drug interactions involving antipsychotics and antihypertensives. Expert opinion on drug metabolism & toxicology, 18(4), 285-298.
- Monteith, S., & Glenn, T. (2019). A comparison of potential psychiatric drug interactions from six drug interaction database programs. Psychiatry research, 275, 366-372.
- Alpert, J. E. (2015). Drug-drug interactions in psychopharmacology. Massachusetts General Hospital Psychopharmacology and Neurotherapeutics, 113-127.

Balancing Factors In Drug Recommendations

Genotype Risk	
Consider Alternatives	3
Use with Caution	2
Standard Precautions	0

DDI Risk	
Contraindicated	5
Major	3
Moderate	2
Minor	1
No Interaction	0

Previous Response	
Negative Response	5
Unknown	0.5
Positive Response	0

Best Medication = Minimum(Genotype Risk+ DDI Risk + Previous Response)

Future Work

Future Work

- Collaboration with Clemson-MUSC AI hub
  - Publication field-area expertise
  - Computation resources to continue training
  - Publication
- Model Optimization
- Train severity model using new methods

- Integrate MEDIC database into reports
- Integrate drug alternatives into report workflows
- Resolve ambiguous interactions
  - “Risk of Adverse Side Effects” is most common type of interaction, but is not specific

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MEDIC Refinement

- Due to the composite nature of the database, there is some missing information across the 1.2 million DDI pairs
- Resolving this missing information is not only a continuing project, but also a common issue in the field

A comparison of potential psychiatric drug interactions from six drug interaction database programs

Scott Monteith [a], Tasha Glenn [b]

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https://doi.org/10.1016/j.psychres.2019.03.041 Get rights and content

Highlights

- Compared category of potential DDI from 6 drug interaction database programs.
- Searched 100 drug interaction pairs containing psychiatric drugs.
- Overall percent agreement was 66%; overall Fleiss kappa interrater reliability was fair.
- Potential DDI categories from drug interaction database programs often differ.

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MEDIC Refinement

- Resolve missing severity information
- Use new versions of databases to improve training
  - Less gaps, more information
- Can be helped by applying the next project

JOURNAL ARTICLE

DrugBank 6.0: the DrugBank Knowledgebase for 2024

Craig Knox, Mike Wilson, Christen M Klinger, Mark Franklin, Eponine Oler, Alex Wilson, Allison Pon, Jordan Cox, Na Eun (Lucy) Chin, Seth A Strawbridge ... Show more

Nucleic Acids Research, Volume 52, Issue D1, 5 January 2024, Pages D1265–D1275, https://doi.org/10.1093/nar/gkad976

Published: 11 November 2023 **Article history**

PRECISION GENETICS

DrSyn

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DrSyn Overview

- Software that identifies drugs based on their name, including all the synonyms
  - Aspirin, acetylsalicylic acid, Bayer aspirin, etc.
- Similar software is sold by DrugBank, GoodRx, etc.

Premium Modules *(each licensed separately)*	US	Canada (English Language)	Canada (French Language)
CPOE and Order Entry			
-FDB OrderKnowledge®	✓	✓	
Interoperability			
Interoperability Module™ Core Package	✓	Not applicable	Not applicable
Interoperability Module™ Enhanced Package**	✓	Not applicable	Not applicable
SNOMED CT (Canada)		✓	
Canadian Clinical Drug Interoperability Module™		✓	✓

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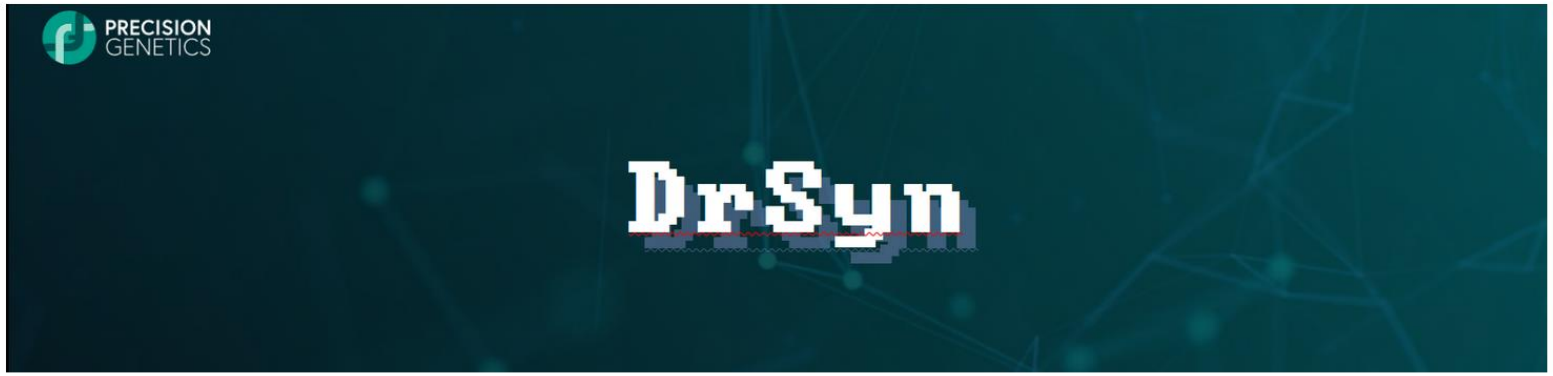
DrSyn Updates

- Rebuild of Drug Library
  - NLM, NIH, PubChem, MeSH
- Added Precision Genetics Drug ID (PGDID) Generation and Mapping
  - Allows for unique IDs for each drug in the library
  - Ability to be updated without affecting current identification mapping
  - Reads library, finds new drugs present, creates new PGDID's, updates ID list
- Improved matching algorithm
- Implemented drug recognition module

DrSyn Updates

- Side by side performance testing with another similar utility
  - Fast Data Science Named Drug Entity Recognition
- Major improvements within source code optimization and documentation
- Creation of Jupytr Notebook for guiding users on proper usage
- Packaging the program and a public beta pre-release on GitHub

README MIT license



DrSyn: A Python Package for Drug Name Identification and Standardization

DrSyn is a powerful Python package designed to identify drug names within medical texts, extract them, and convert them to their common names based on MeSH standards. This tool is essential for standardizing drug names across various textual sources, making it invaluable for both healthcare and research purposes.

Key Features:

- **Robust Drug Name Recognition**: Accurately identifies drug names in medical texts, ensuring comprehensive extraction.
- **MeSH Standard Conversion**: Converts extracted drug names to their common or generic names, adhering to MeSH standards.
- **Extensive Synonym Library**: Utilizes a robust and accurate synonym library with data sourced from PubChem, maintained by NCBI.
- **Versatile Text Processing**: Capable of processing individual sentences or multiple documents to extract and standardize drug names.
- **Enhanced Search Capability**: Includes a `pg_lookup` feature for searching specific drug names or Precision

Easy To Use and Fast

Recognizing drugs within sentences, paragraphs, or the text of a single document

In [4]:

```
# Test recognize_drugs_in_text
print("Testing recognize_drugs_in_text...")
recognized_drugs = DrSyn.recognize_drugs_in_text(sample_text)
print("Recognized drugs in text:")
for common_name, pgid in recognized_drugs:
    print(f"Drug: {common_name}, PGID: {pgid}")
```

```
Testing recognize_drugs_in_text...
Recognized drugs in text:
Drug: aspirin, PGID: PGDID1906452
Drug: acetaminophen, PGID: PGDID84099
Drug: naproxen, PGID: PGDID1001887
Drug: desvenlafaxine, PGID: PGDID1607287
Drug: ibuprofen, PGID: PGDID217514
Drug: amphetamine, PGID: PGDID2062818
Drug: duloxetine, PGID: PGDID698212
Drug: sertraline, PGID: PGDID734610
```

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A Note About The Metrics

- Sentence
  - He uses Singulair and Advair for his allergies.
- Expected Drugs
  - Montelukast & Fluticasone
- Found Drugs
  - Montelukast & Fluticasone-Salmeterol
- Advair is Fluticasone-Salmeterol
  - We are performing better than the metrics will show and Fast Data Science is performing worse due

Fast Data Science

fastdatascience.com

You can run the walkthrough Python notebook in Google Colab with a single click: Open in Colab

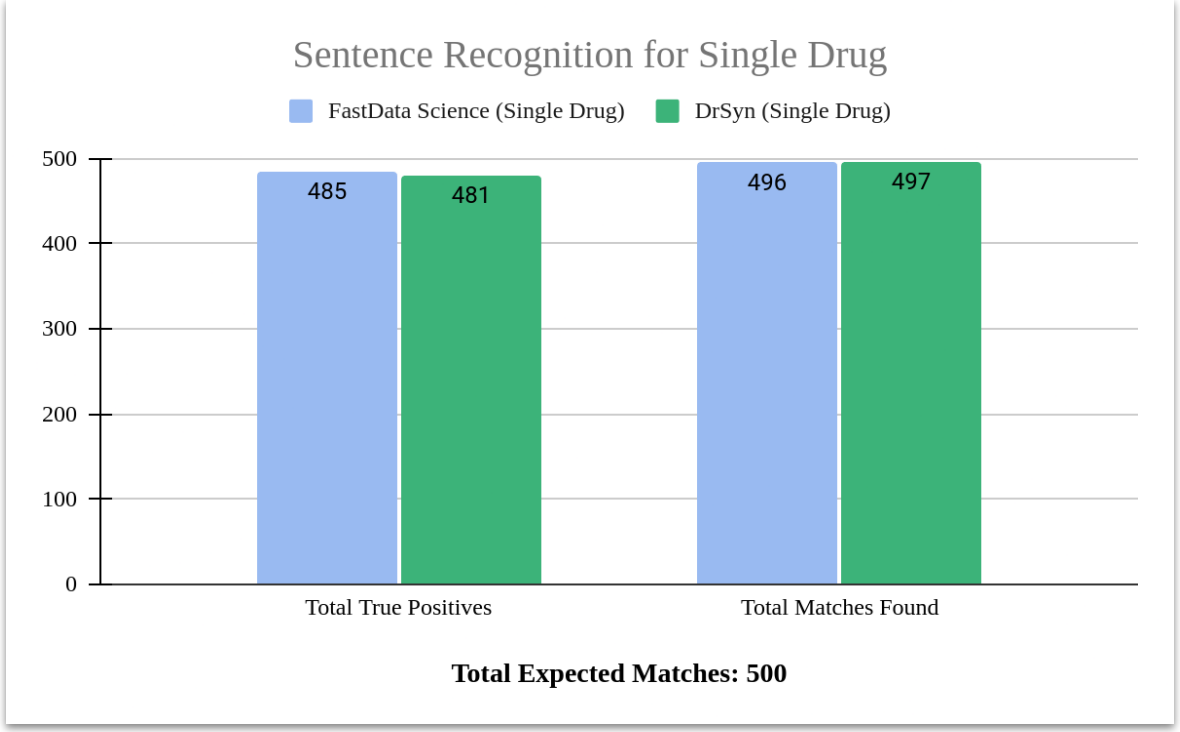
Drug named entity recognition Python library by Fast Data Science

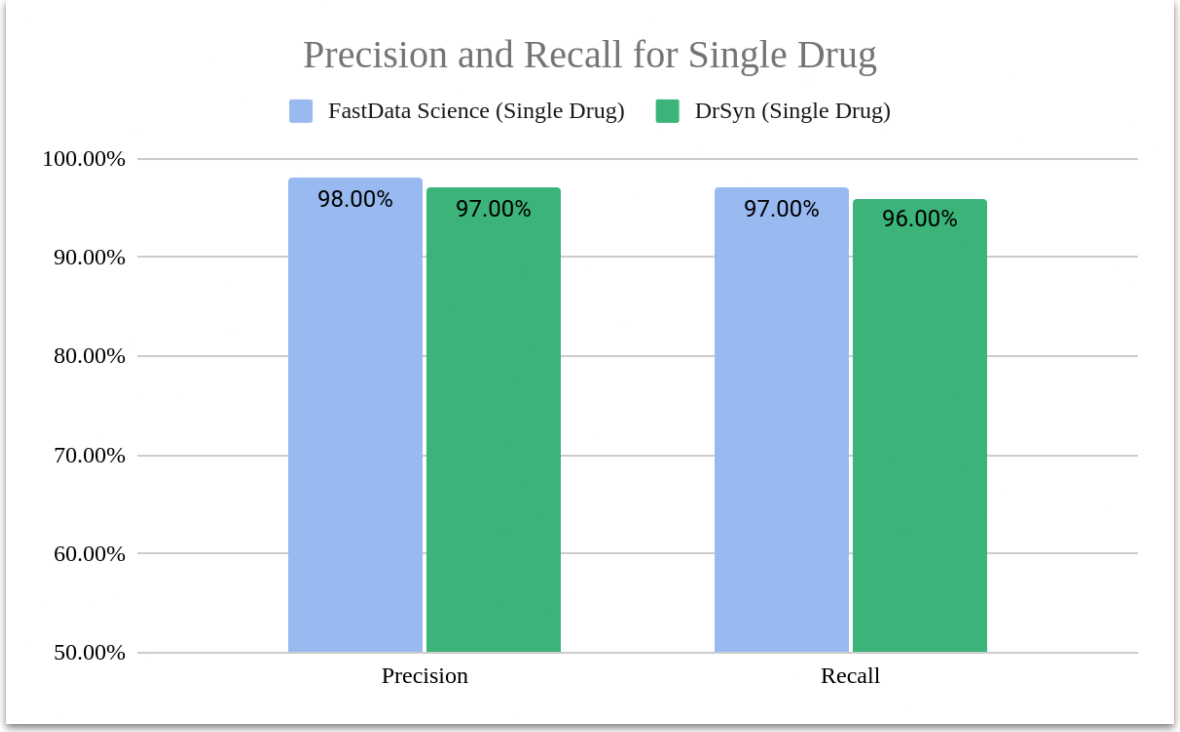
Status In Development | pip install drug named entity recognition | version v1.0.3 | license MIT | pypi v1.0.3 | version v1.0.3

pip downloads 72k | Forks 6

Comparative Performance: DrSyn vs. FastData Science

-Single Drug Recognition Results-

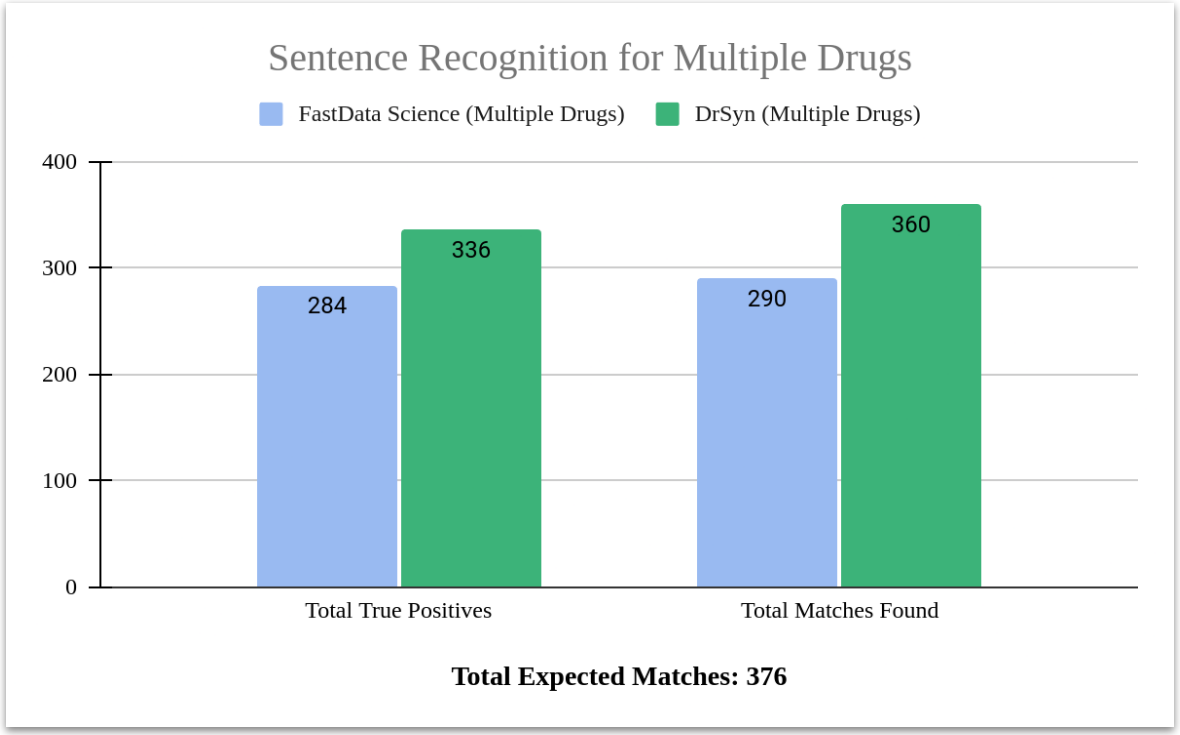




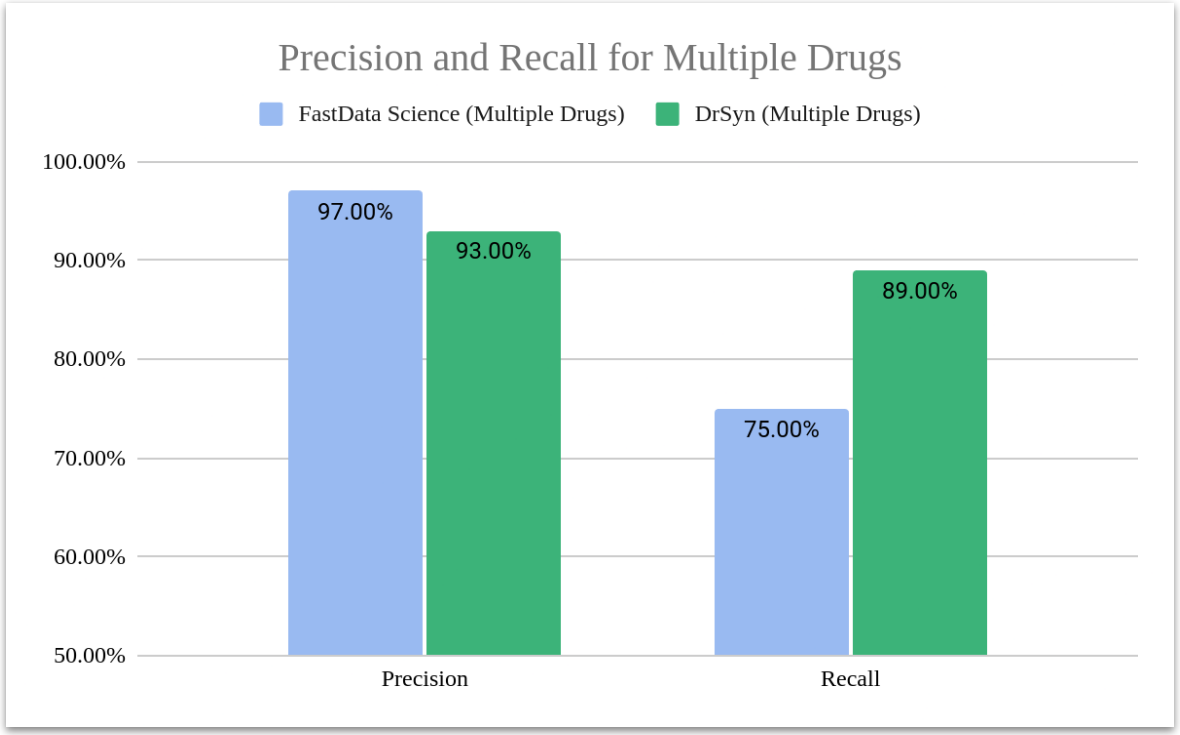
PRECISION GENETICS

Comparative Performance: DrSyn vs. FastData Science

-Multiple Drug Recognition Results-



Total Expected Matches: 376



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Highlights

- Massive drug-synonym library
- Outperforms competition in general recognition
- DrSyn recognizes multiple drugs in texts
- Fast Data Science struggles with drugs in a sentence adjacent to special characters (, | . | :)
- FastData Science maps various drugs incorrectly
  - Vicodin mapped to Acetaminophen

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Future Work

- Apply to InfoMedEx MEDIC Database to help resolve missing data
- Promotion of the DrSyn tool package
- Bug testing and improvement based off feedback
- Full production release for professional implementation

Informed is InfoMedEx

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