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HTS-likeness: physicochemical parameters to create libraries

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Design steps of general purpose HTS library creation

Physicochemical filters

drug-/lead-likeness to select favorable compounds

Structural filters/predictive models

to remove compounds potentially toxic, unstable, reactive, false positives, etc

Diversity selection

to better cover available chemical space





Physicochemical rules/filters/predictive models

	Lipinski	Oprea	Oprea	Walters
		drug-like	lead-like	
acceptor count	<= 10	2-9	0-8	<= 10
donor count	<= 5	0-2	0-5	<= 5
logP	<= 5		-3.5 - 4.5	-5 - 5
molecular weight	<= 500		<= 450	200 - 500
RTB		2-8		<= 8



drugs/drug candidates oral bioavailability

leads capacity for optimization

Ideal general purpose HTS library

- small
- high chances to find hits
- return true hits for variety of assays
- no promiscuous compounds
- soluble
- stable

minimum set of requirements

PubChem data set

94 PubChem assays

	number of assays				
assay type	training set	test set			
cell-based	27	20			
biochemical	22	21			
other	0	3			
total	49 45				
compounds	230 325	72 760			
hit rates, %	0.004-5.10	0.014-2.55			

no PAINS, no frequent hitters

Compounds are from MLSMR library which was created using different strategies of compounds selection (including physicochemical filters and diversity selection)

Physicochemical parameters

Physicochemical properties calculated with RDKit

- H-bond donors count (HBD)
- H-bond acceptors count (HBA)
- Complexity = HBD + HBA
- logP
- MW
- Topological polar surface area (TPSA)
- Rings count (NumRings)
- Rotatable bonds count (RTB)

Enrichment
$$= \frac{\text{hit rate for selected compounds}}{\text{baseline hit rate}}$$

PubChem training set

Distribution of median enrichment vs. values of physicochemical parameters



binned physicochemical parameters

Manually derived rules from the PubChem training set

	all	biochemical	cell-based	Lipinski	Oprea DL	Oprea LL	Walters
complexity	5-10	5-10	3-10				
acceptor count	3-8	4-8	3-8	<= 10	2-9	<= 8	<= 10
donor count	0-2	0-4	0-2	<= 5	<= 2	<= 5	<= 5
logP	3-6	1-6	>3	<= 5		-3.5 - 4.5	-5 - 5
molecular weight	250-550	200-550	300-600	<= 500		<= 450	200 - 500
Ring count	3-5	2-5	3-6				
RTB	1-7	1-6	3-9		2-8		<= 8
TPSA, A^2	15-135	30-150	15-135				

Application of the derived rules to the test set

mula cat	number of	datasets median enrichment			
selected compounds		all	biochemical	cell-based	
all	14 852 (20.4%)	1.18	1.15	1.24	
biochemical	26 407 (36.3%)	1.01	1.06	0.99	
cell-based	21 941 (30.2%)	1.00	1.05	0.93	

Random forest model



Random subsample = 2/3 Nvars = 3 Ntrees = 250 min_parent_samples = 3000 min_child_samples = 1000



PubChem test set prediction

Manually derived rules

mula cot	number of	datasets median enrichment				
Tule set	selected compounds	all	biochemical	cell-based		
all	14 852 (20.4%)	1.18	1.15	1.24		
biochemical	26 407 (36.3%)	1.01	1.06	0.99		
cell-based	21 941 (30.2%)	1.00	1.05	0.93		

Random Forest prediction

model	number of	dataset median enrichment				
Inoder	selected compounds	all	biochemical	cell-based		
all assays	20 337 (28.0%)	1.34	1.15	1.45		
biochemical assays	12 528 (17.2%)	1.36	1.38	1.27		
cell-based assays	29 179 (40.2%)	1.16	1.08	1.36		

Common physicochemical filters

mile cot	number of	datasets median enrichment				
rule set	number of datasets median enricition selected compounds all biochemical 61 624 (84.8%) 0.98 1.00 55 984 (77.0%) 0.95 0.92 50 566 (69.5%) 0.99 1.01 57 533 (79.1%) 1.02 1.05	cell-based				
Lipinski	61 624 (84.8%)	0.98	1.00	0.98		
Oprea drug-like	55 984 (77.0%)	0.95	0.92	0.97		
Oprea lead-like	50 566 (69.5%)	0.99	1.01	0.89		
Walters	57 533 (79.1%)	1.02	1.05	1.03		

NCI60

	NCI60 data set (-logGI ₅₀)
inactive threshold	<= 5
active threshold	> 7
number of assays with > 9000 compounds tested	68
number of compounds in the data set	46 982
hit rates	1.4% - 6.1%

NCI60 prediction

Common physicochemical filters

rule set	number of selected compounds	median enrichment
Lipinski	34 497 (73.4%)	0.97
Oprea drug-like	26 951 (57.4%)	1.03
Oprea lead-like	29 295 (62.4%)	0.98
Walters	32 824 (69.9%)	1.00

Manually derived rules

rule set	number of selected compounds	median enrichment		
all	7 043 (15.0%)	1.07		
biochemical	13 232 (28.2%)	1.03		
cell-based	9 080 (19.3%)	1.03		

Random Forest prediction

model	number of selected compounds	median enrichment
all assays	18 525 (39.4%)	1.29
biochemical assays	16 412 (34.9%)	1.65
cell-based assays	23 258 (49.5%)	1.52

Quantitative estimate of drug-likeness (QED)

ARTICLES

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nature chemistry

Quantifying the chemical beauty of drugs

G. Richard Bickerton¹, Gaia V. Paolini², Jérémy Besnard¹, Sorel Muresan³ and Andrew L. Hopkins^{1*}

Table 1 | Optimized desirability function weightings by Shannon entropy.

	Shannon entropy	Rank	Mr	ALOGP	HBD	HBA	PSA	ROTB *	AROM*	ALERTS
QED _{w,max}	293.42	1	0.50	0.25	0.50	0.00	0.00	0.50	0.25	1.00
QED _{w,mo}	293.03	1-1000	0.66	0.46	0.61	0.05	0.06	0.65	0.48	0.95
QED _{w,u}	283.08	81,657	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

data set	median enrichment at QED / coverage				
	>= 0.5	>= 0.6	>= 0.7	>= 0.8	>= 0.9
PubChem training set	0.90/0.82	0.83 / 0.67	0.76 / 0.46	0.66 / 0.24	0.59 / 0.04
PubChem test set	0.93 / 0.74	0.87 / 0.58	0.76/0.39	0.77/0.19	0.53 / 0.04
NCI60	0.60/0.55	0.53 / 0.38	0.56 / 0.23	0.38/0.09	0.42/0.01

Conclusion

- HTS-like chemical space is partially overlapped with a drug-like chemical space
- HTS-likeness rules may reduce the size of a library and improve hit rates relatively to drug-likeness filters
- Random Forest models more accurately estimate HTS-likeness than manually derived rules

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