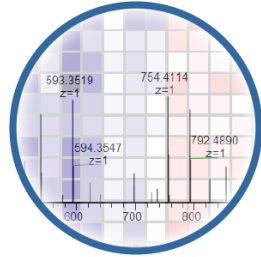


Library of Integrated Network-based Cellular Signatures



Proteomic Characterization Center
for Signaling and Epigenetics

Strange and Wonderful Observations from the World of Proteomic Profiling

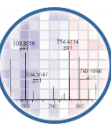
September 19, 2016

Jacob D. Jaffe – Broad Institute, PI

Li-Huei Tsai – MIT, co-investigator

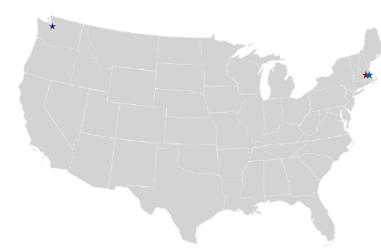
Michael MacCoss – U. of Washington, co-investigator

Outline



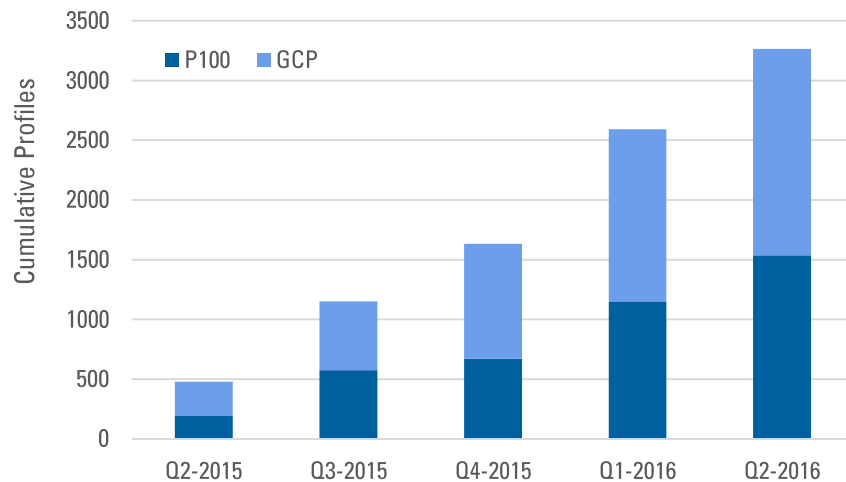
- Profiling and Infrastructure Progress
- Assessment of dataset quality
- Vignettes
- Extension into neuronal models
- Unlocking deeper signaling information through next-gen MS
- Outreach Activities

Extensive progress building the library

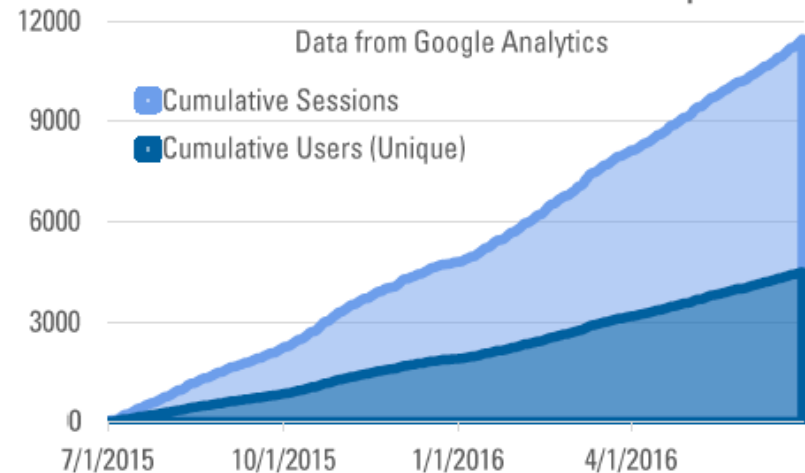


- 3400+ biological samples generated spanning:
 - 90 compounds in triplicate spanning many MoA
 - Beginning CRISPR/Cas9-based gene disruptions
 - 6 cellular models (breast, lung, skin, prostate, and pancreatic cancers; neuronal precursors)
 - 2 assay platforms (+L1000 in collaboration)
- Key infrastructure:
 - Public data repository with built-in signature visualization (bit.ly/PCCSEData)
 - Documented workflows; automated analytical pipeline for reproducibility

LINCS PCCSE Profiles Released

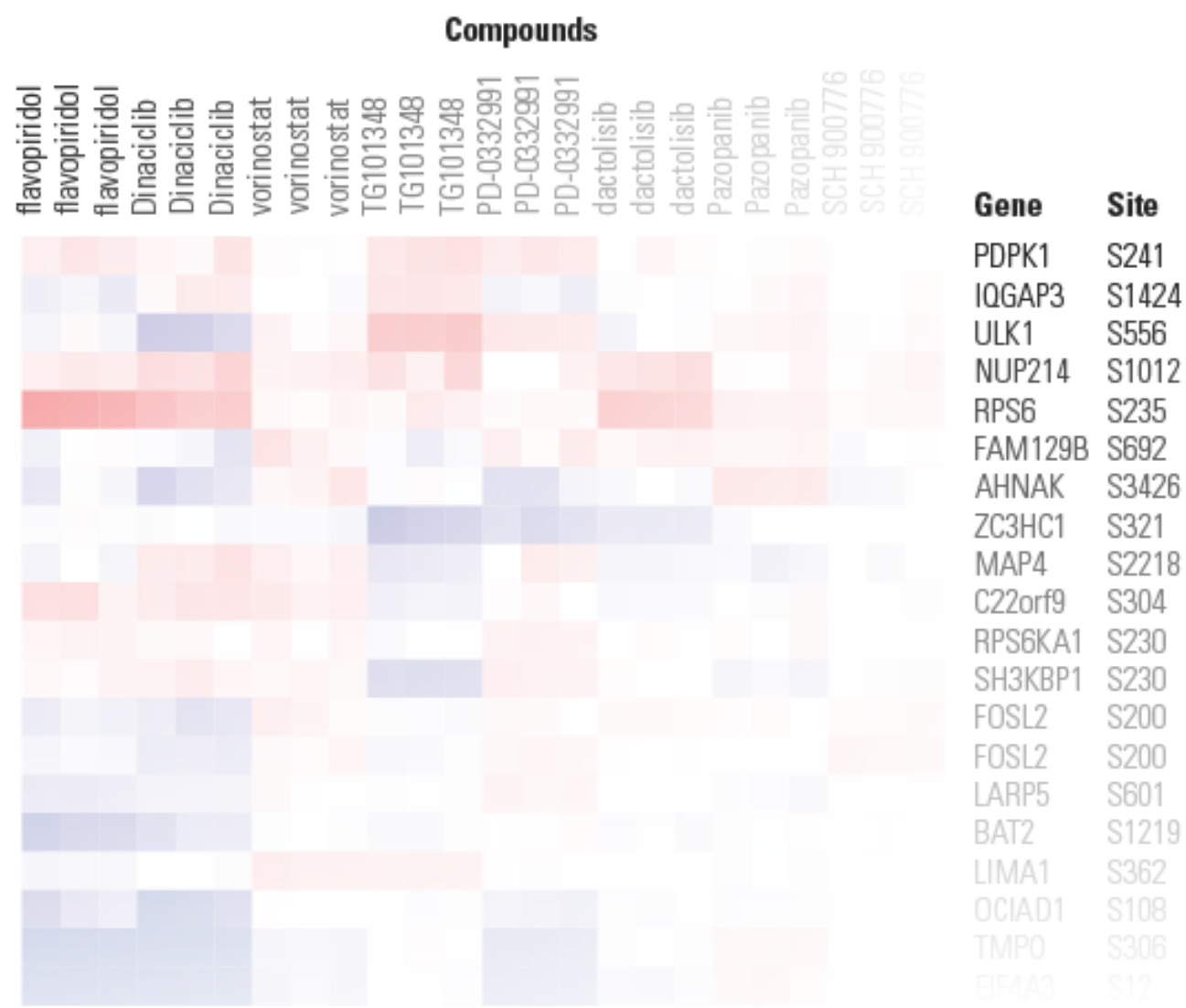


PCCSE Cumulative Data Consumption



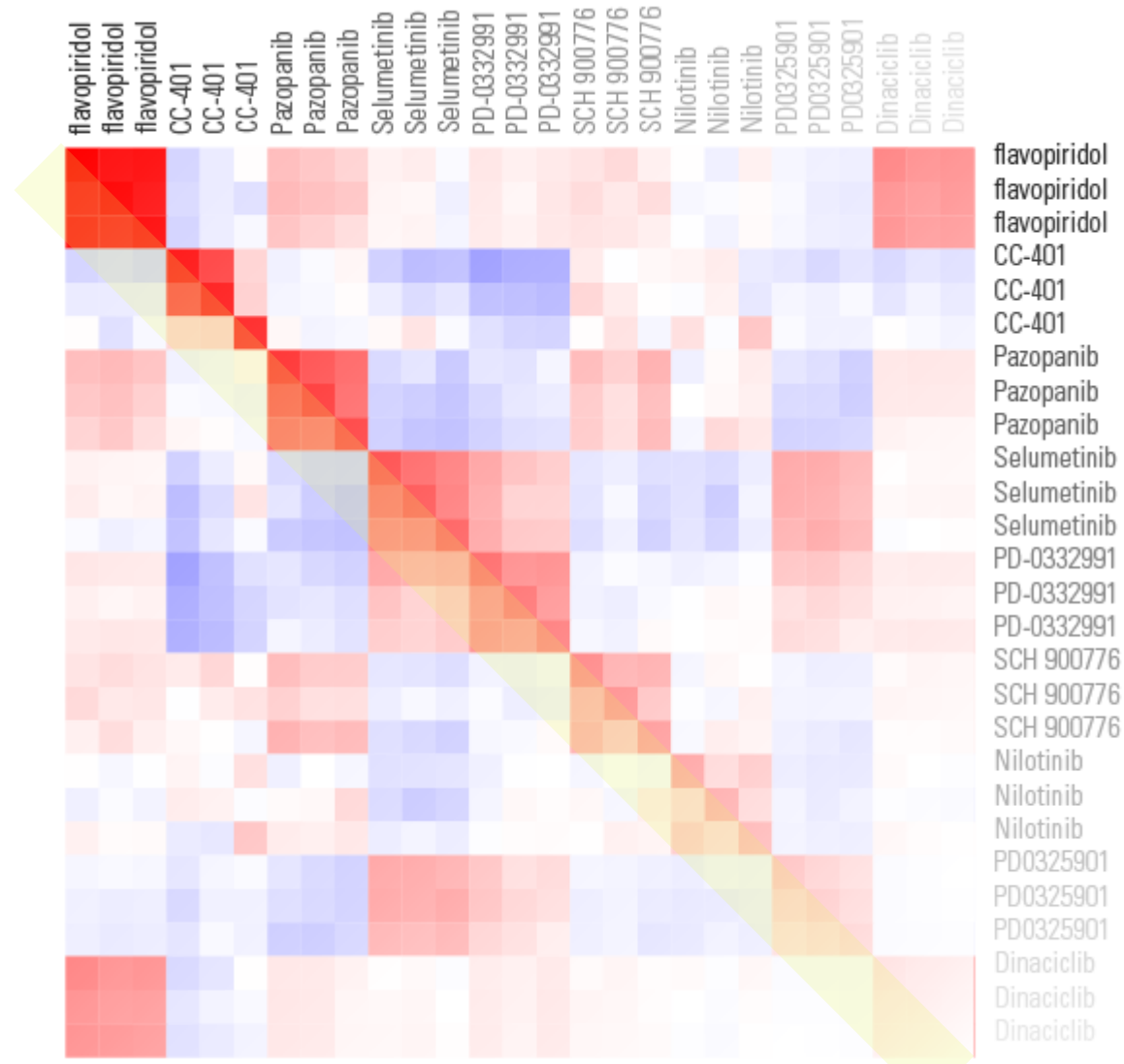
Turning signatures into connections: Signatures

Signatures are groups of related profiles



Turning signatures into connections: Similarities

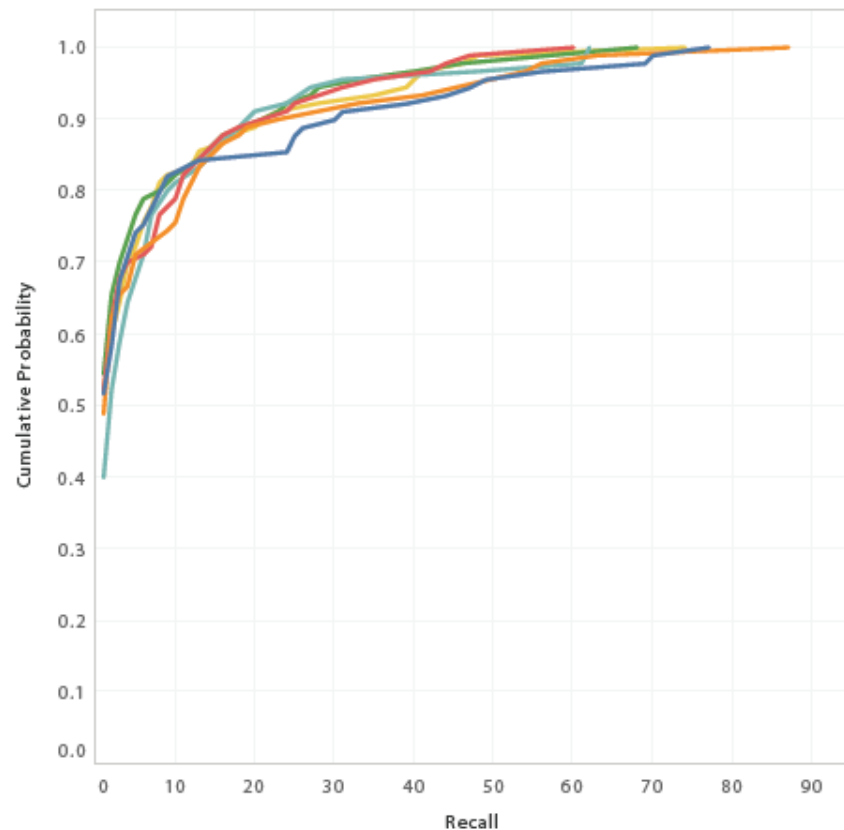
Similarities are correlations computed from signatures



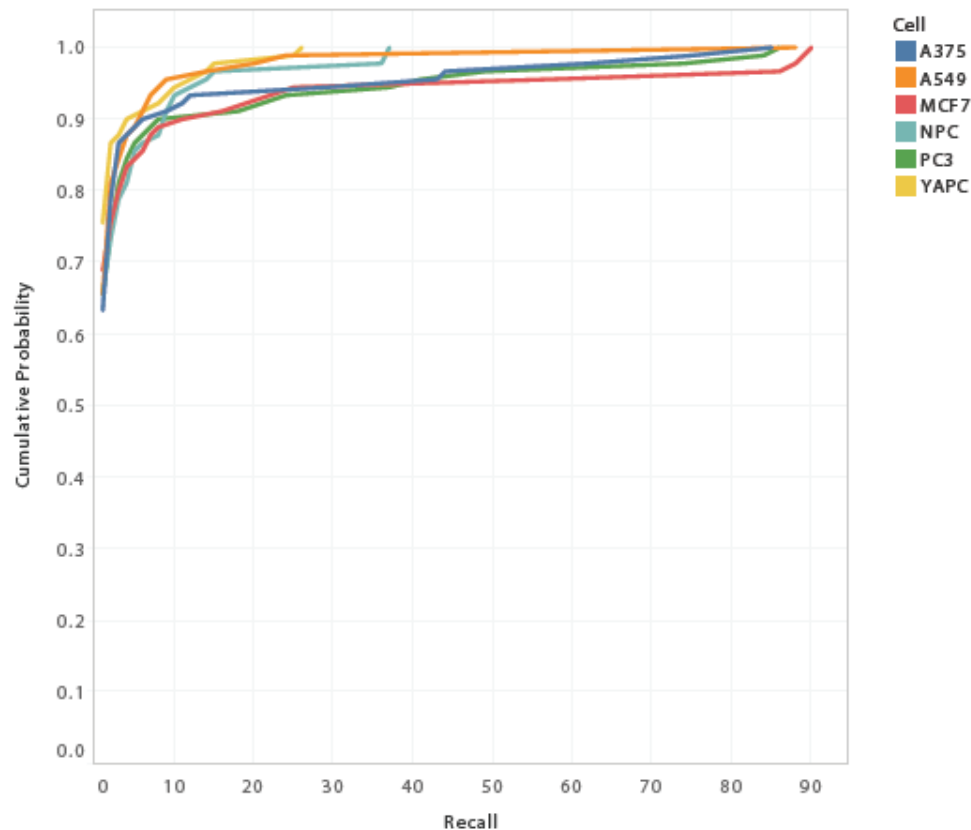
Replicate consistency describes similarity on the lower diagonal

Consistency rank via similarity assesses dataset quality

GCP



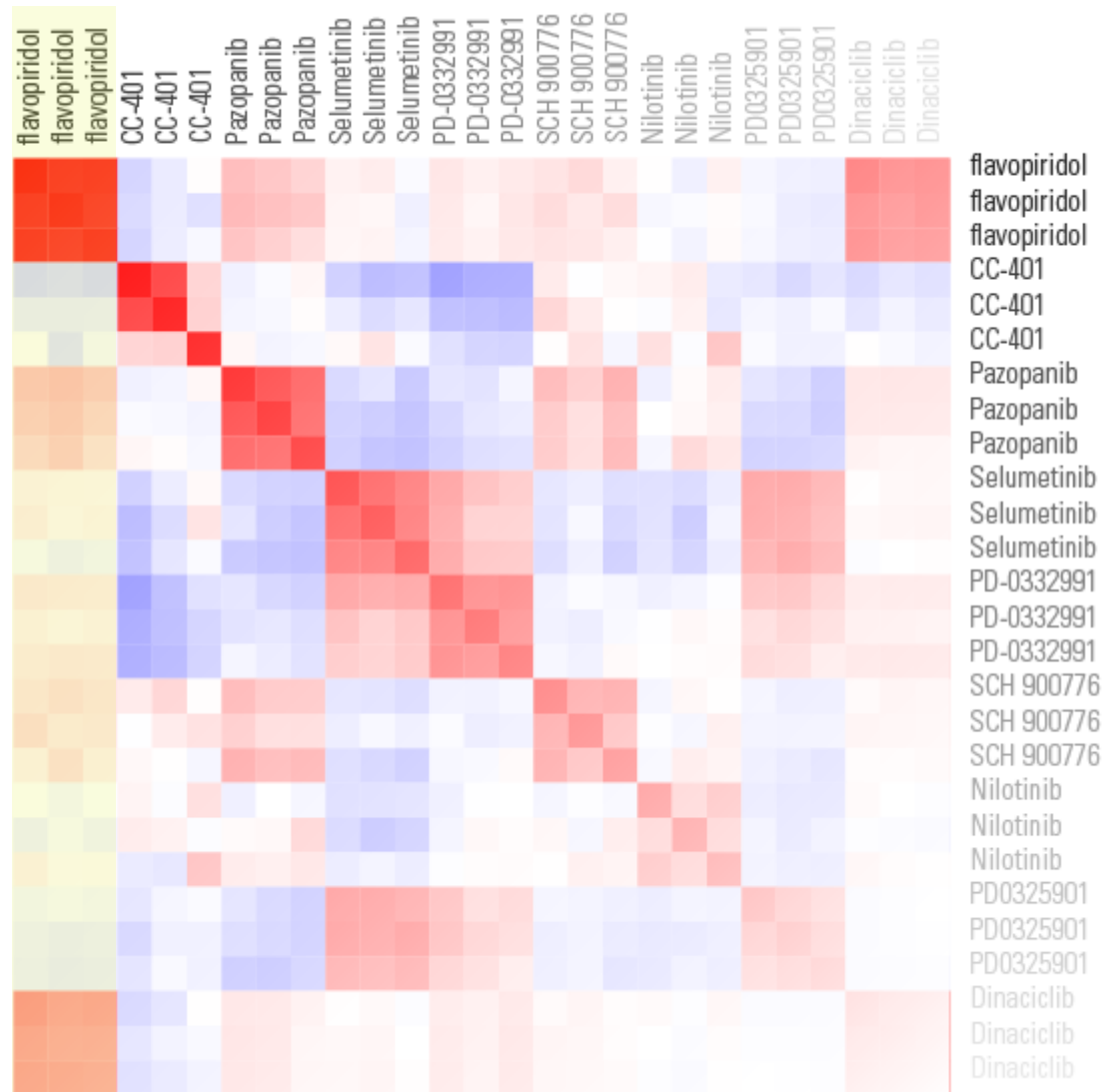
P100



- Average AUC: GCP ~92%, P100 ~96%
- 66% of compounds have signal in GCP (within top 3 recall rank)
- 83% of compounds have signal in P100 (within top 3 recall rank)

Turning signatures into connections: Connectivity

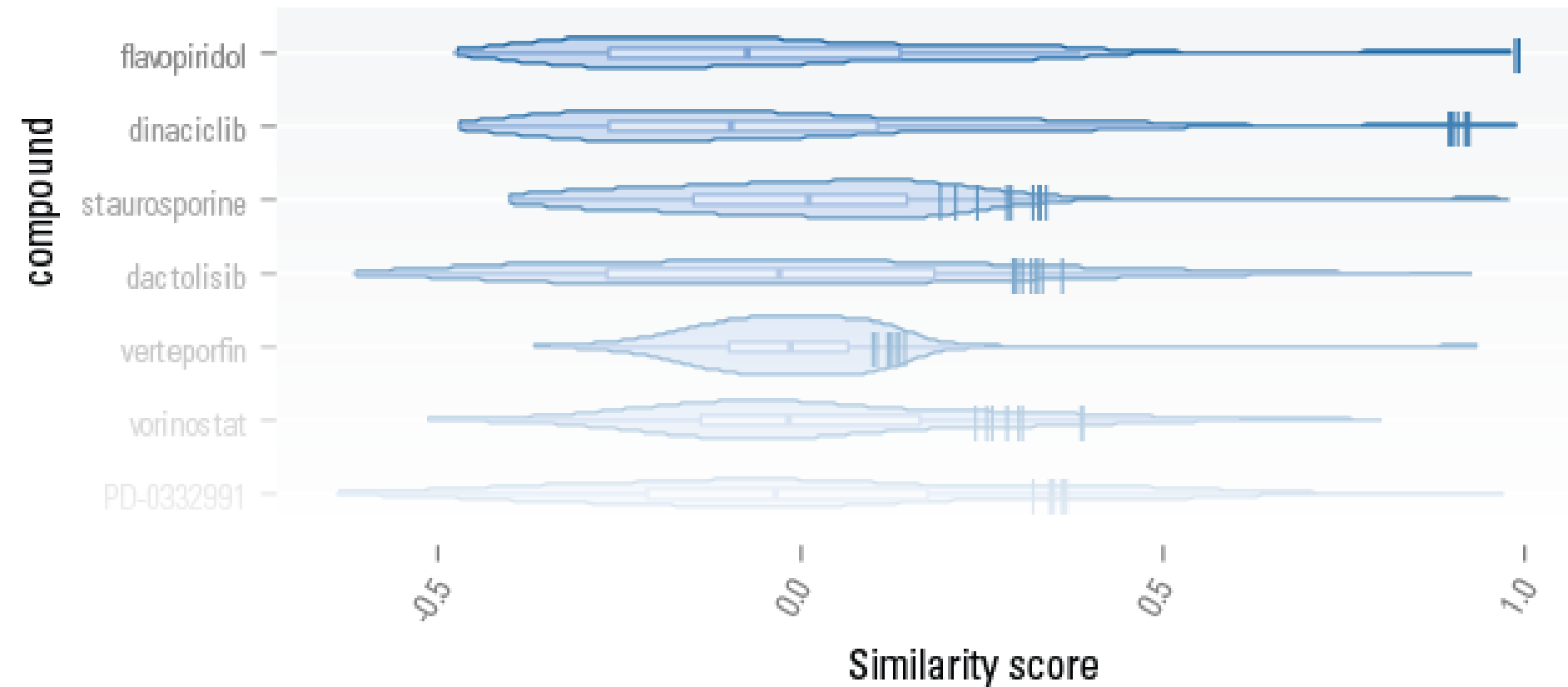
Similarities are correlations computed from signatures



Connectivity comes from analysis of the similarity matrix

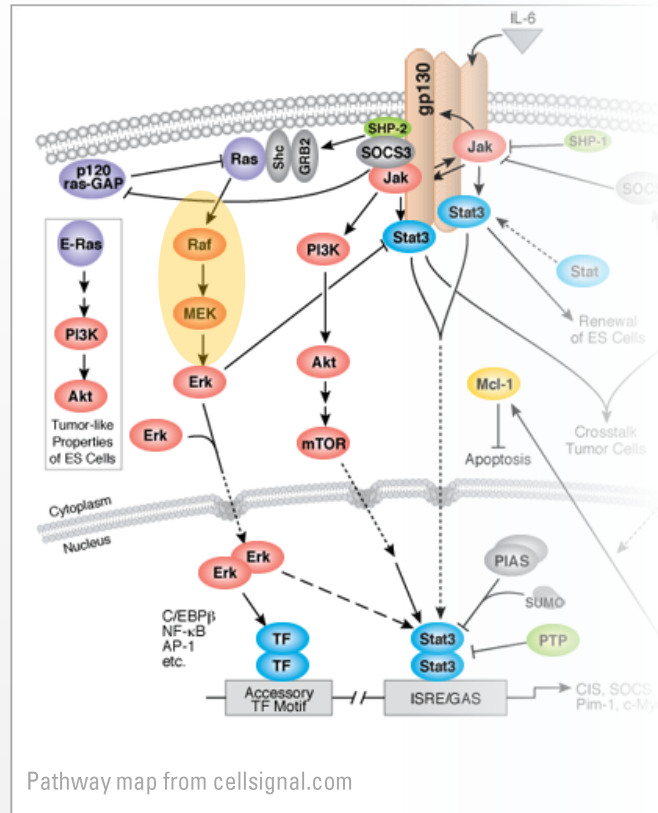
Turning signatures into connections

Connectivity queries put correlations in context



The **connectivity score** is a signed value of the KS-test

Vignette 1: What's a BRAF inhibitor to do when its target is not a dependency?



P100 Connectivities

Query drug

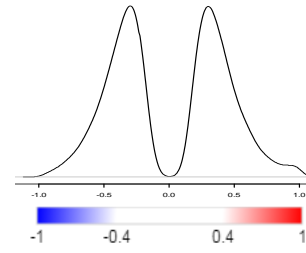
Cell type

Query drug	A375	vemurafenib
Cell type	A375	vemurafenib
A549		
MCF7		
NPC		
PC3		
YAPC		

Target drug

Drug Class

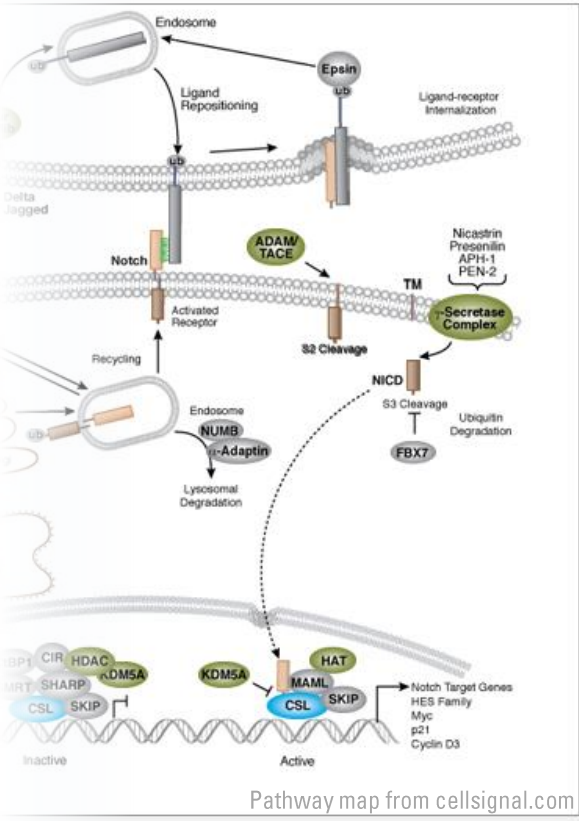
vemurafenib	singleton	0.85	1%
Selumetinib	Mek inhibitor		
PD0325901	Mek inhibitor	0.63	5%
staurosporine	singleton		
sirolimus	mTOR inhibitor	0.52	10%
Everolimus	mTOR inhibitor		
dexamethasone	Steroid receptor agonist		
OSI-027	mTOR inhibitor		
LY-294002	PI3K inhibitor		
KN-93	CaMK inhibitor		
CHIR99021	GSK3 inhibitor		
RGFP966	HDAC inhibitor		
Compound E	gamma secretase inhibitor		
Gossypetin	HDAC activator		
Pazopanib	singleton		



Score Percentile

- **A375** has mutant BRAF (V600E) and is dependent on it
- Vemurafenib is the top ranked connection ALL **cancer** lines
- **NPCs** do not seem to respond at all
- *So what does it do in the other cell lines?*

Vignette 1: What's a BRAF inhibitor to do when its target is not a dependency?



Pathway map from cellsignal.com

P100 Connectivities

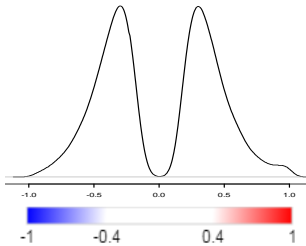
Query drug

Cell type

Target drug

Drug Class

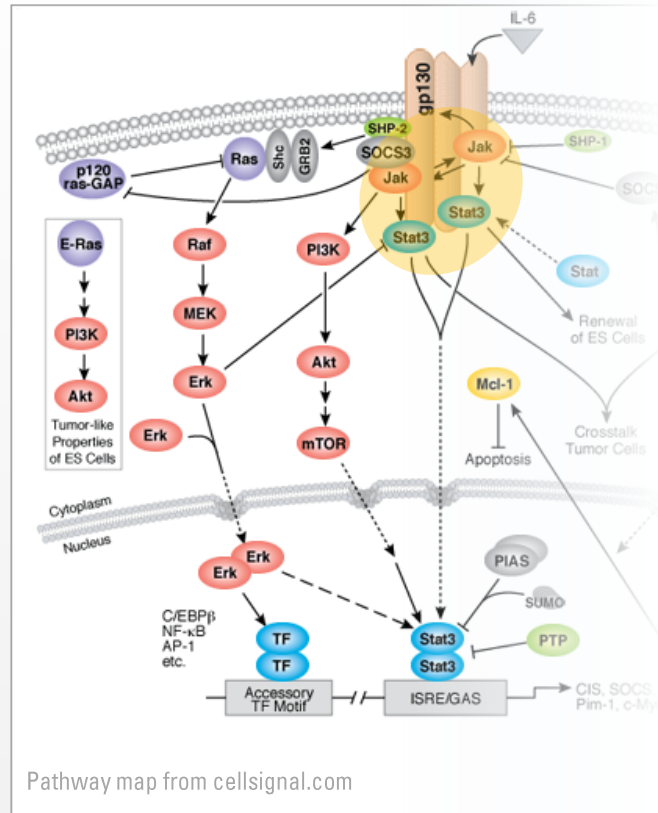
Query drug	Cell type	Target drug	Drug Class
A375	vemurafenib	vemurafenib	singleton
A549	vemurafenib	BMS-906024	Notch pathway inhibitor *
MCF7	vemurafenib	Ginkgetin	HDAC activator*
PC3	vemurafenib	1271738-62-5	Acetyltransferase inhibitor*
YAPC	vemurafenib	calpain inhibitor II	singleton
		Tofacitinib	Jak/Stat inhibitor
		UNC1215	singleton
		IPI145	PI3K inhibitor
		RO4929097	Notch pathway inhibitor *
		Verteporfin	singleton
		Olaparib	singleton
		Rolipram	singleton
		Pravastatin	Jak/Stat inhibitor
		RGFP966	HDAC inhibitor
		Compound E	gamma secretase inhibitor



Score	Percentile
0.85	1%
0.63	5%
0.52	10%

- Does vemurafenib inhibit the **Notch** pathway in **PC3**?

Vignette 1: What's a BRAF inhibitor to do when its target is not a dependency?



P100 Connectivities

Query drug

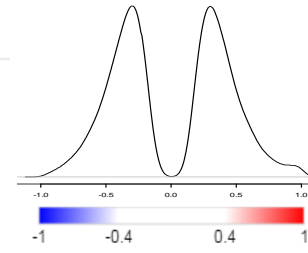
Cell type

Query drug	A375	vemurafenib	A549	vemurafenib	MCF7	vemurafenib	PC3	vemurafenib	YAPC	vemurafenib
Cell type	Blue	Blue	Blue	Blue	Blue	Blue	Blue	Blue	Blue	Blue
Target drug	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
Drug Class	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red

Target drug

Drug Class

vemurafenib	singleton
JQ1-S	BRD inhibitor *
Pravastatin	Jak/Stat inhibitor
GSK525762A	BRD inhibitor *
tacrolimus	singleton
Selumetinib	Mek inhibitor
GSK1210151A	BRD inhibitor *
Verteporfin	singleton
roxolitinib	Jak/Stat inhibitor
decitabine	DNA methyltransferase inhibi
KU-55933	Cell cycle inhibitor
Etoposide	singleton
Tofacitinib	Jak/Stat inhibitor
GSK-J4	Lysine demethylase inhibitor
BMS-906024	Notch pathway inhibitor

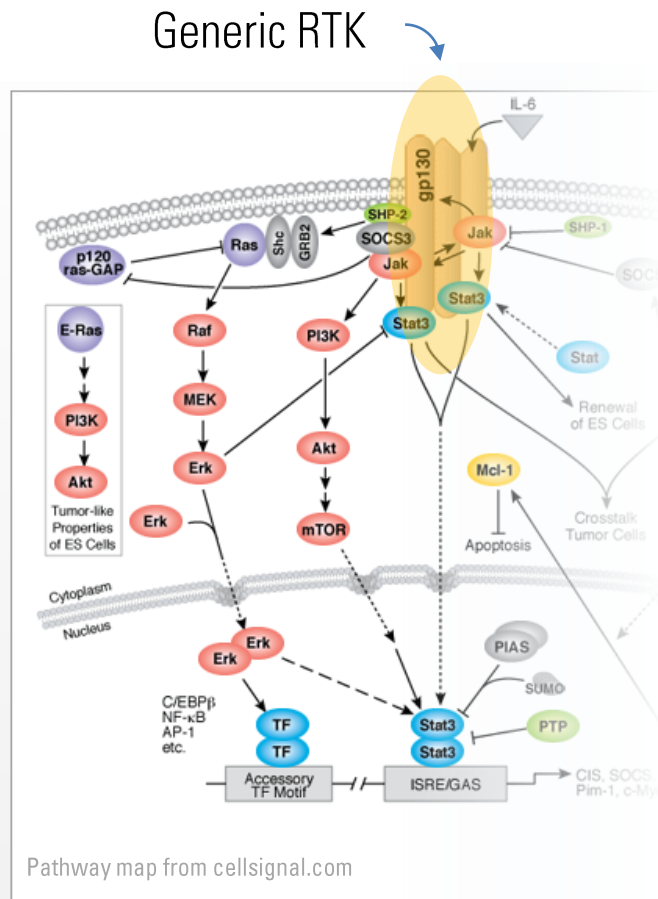


Score	Percentile
-------	------------

0.85	1%
0.63	5%
0.52	10%

- Connections to **BRD inhibitors** seem enriched in **MCF7**?
- Many lines seem to have some residual effects in Jak/Stat, which is ~upstream of RAF

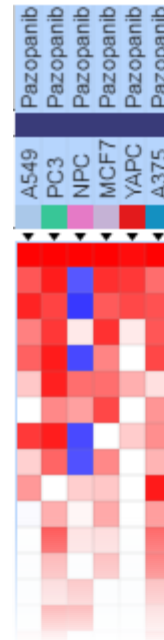
Vignette 2: The strange case of Pazopanib in NPCs



P100 Connectivities

Query drug

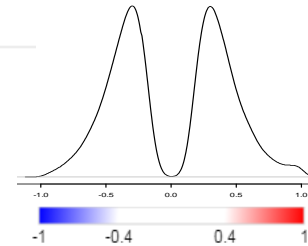
Cell type



Target drug

Drug Class

Pazopanib	singleton
SMER-3	(Ubq E3 ligase inhibitor)
niclosamide	Jak/Stat inhibitor
Resveratrol	Sirtuin inhibitor
Dinaciclib	Cell cycle inhibitor
Nilotinib	(Bcr-Abl inhibitor)
SP600125	Jnk inhibitor
C646 (CHEMBL1797936)	Acetyltransferase inhibitor
SCH 900776	Cell cycle inhibitor
dactolisib	PI3K inhibitor
momelotinib	Jak/Stat inhibitor
Roscovitine	Cell cycle inhibitor
OSI-027	mTOR inhibitor
LY-294002	PI3K inhibitor
staurosporine	singleton



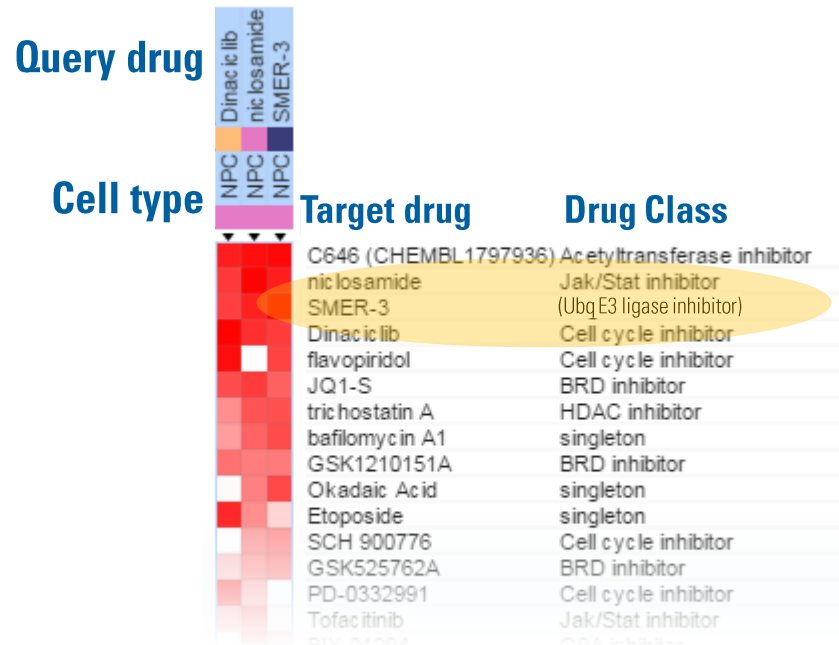
Score	Percentile
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0.85	1%
0.63	5%
0.52	10%

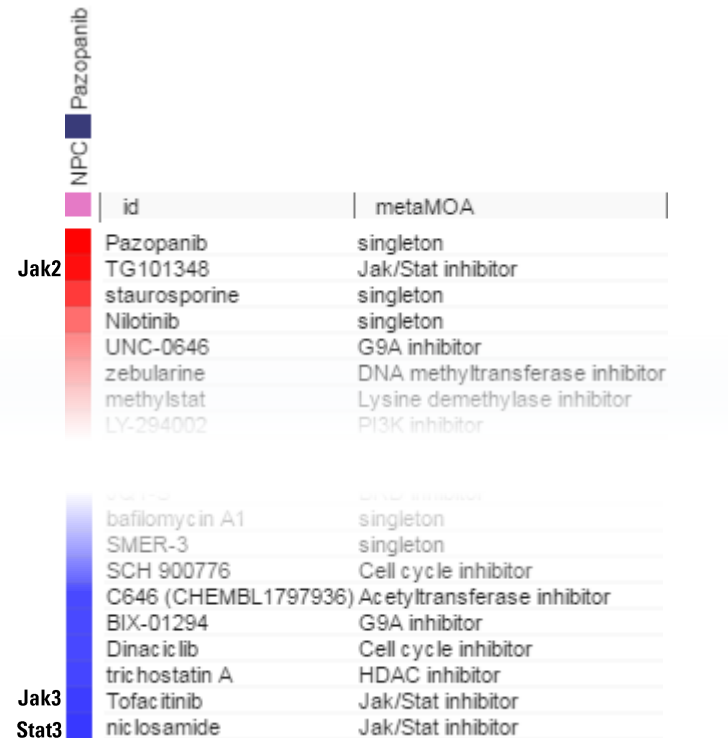
- Pazopanib is the top ranked connection **all lines**
- SMER3, niclosamide, and dinaciclib are strong (+) connections in **cancer** lines
- However, these 3 are **strong (-) connections in NPCs**.

Vignette 2: The strange case of Pazopanib in NPCs

Connectivity of Pazopanib Cancer Connections in NPCs



(+) and (-) Connectivity of Pazopanib in NPCs



- But all of these things are strongly connected in NPCs, just not to pazopanib
- Perhaps Pazopanib has **Jak2** selectivity in NPCs? Or NPCs favor Jak2 signaling?

Vignette 3: Chromatin connections of MEK inhibitors?

GCP Connectivities

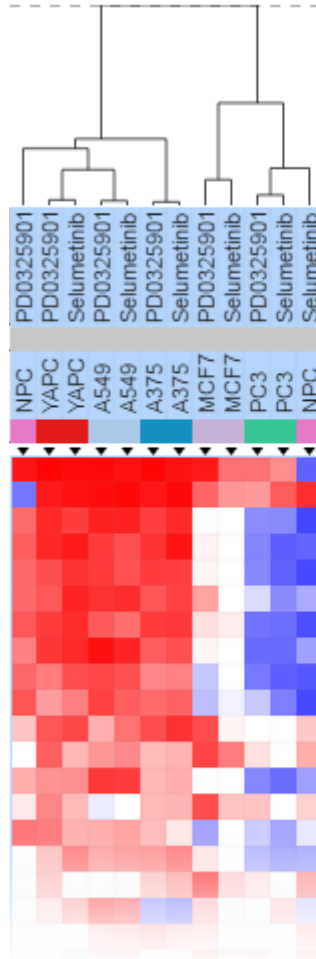


Query drug

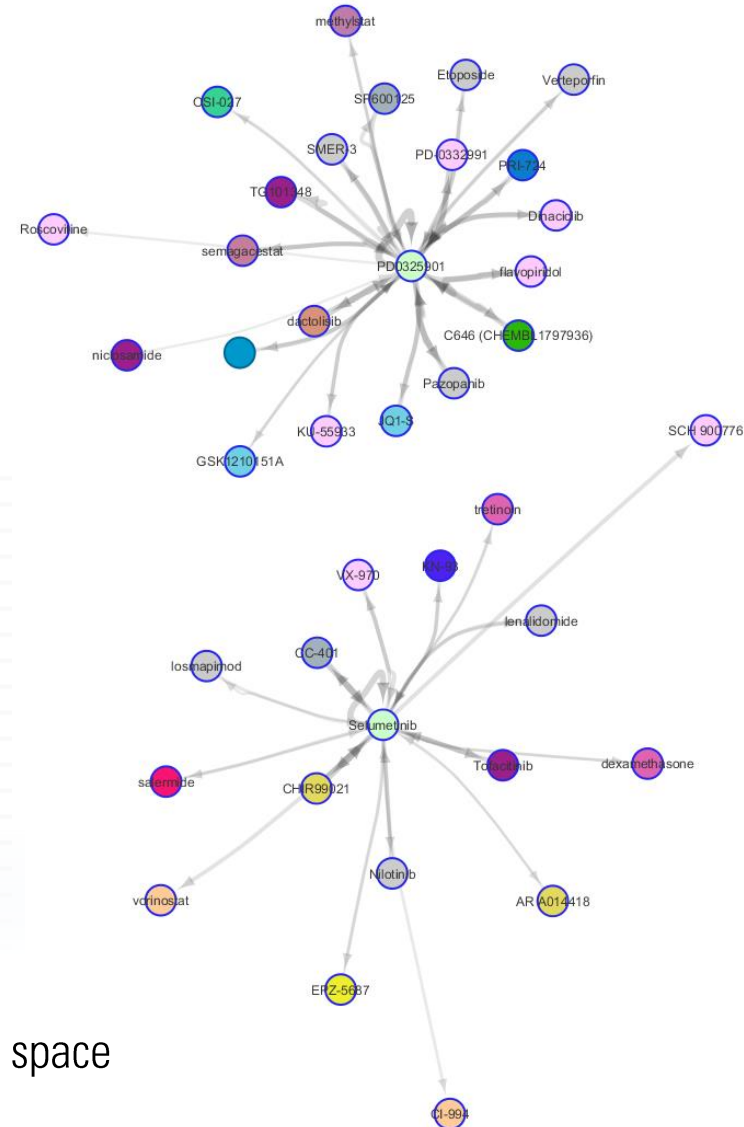
Cell type

Target drug

Drug Class



PD0325901	Mek inhibitor
Selumetinib	Mek inhibitor
TG101348	Jak/Stat inhibitor
PD-0332991	Cell cycle inhibitor
Dinaciclib	Cell cycle inhibitor
Resveratrol	Sirtuin inhibitor
flavopiridol	Cell cycle inhibitor
Etoposide	singleton
SMER-3	singleton
C646 (CHEMBL1797936)	Acetyltransferase inhibitor
trichostatin A	HDAC inhibitor
MS-275	HDAC inhibitor
nic losamide	Jak/Stat inhibitor
belinostat	HDAC inhibitor
KU-55933	Cell cycle inhibitor
staurosporine	singleton
CI-994	HDAC inhibitor
geldanamycin	singleton
RGFP966	HDAC inhibitor



NPC Connectivity networks

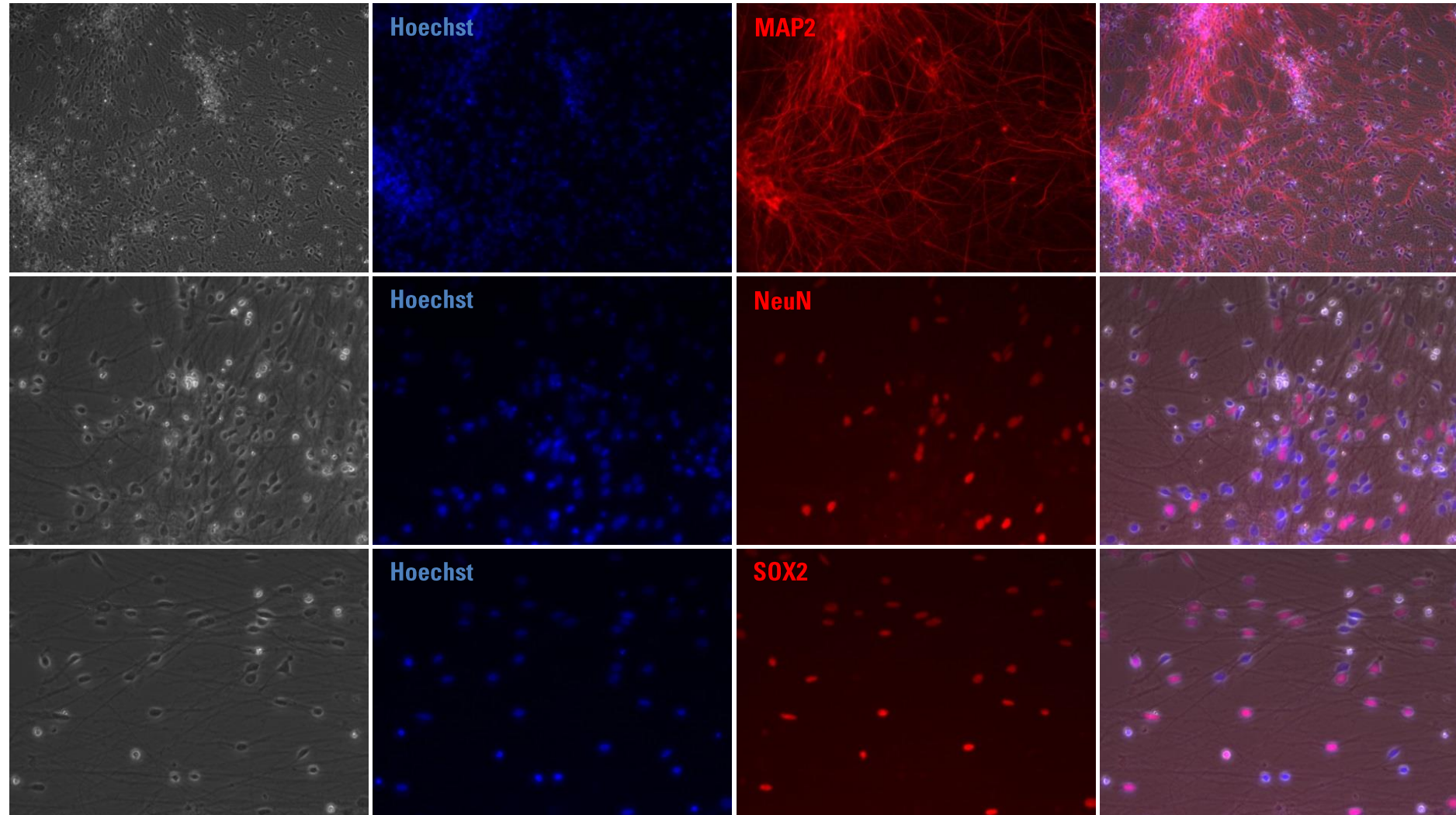
- Mek inhibitors have a “recallable” signature in chromatin space
- 3 basic classes of response as derived from connections
 - Connections to cell cycle drugs suggest arrest, neutrality, and pro-proliferation
 - Again, NPCs show interesting biology with differential connections of PD0325901 and Selumetinib

Preview of the coming year

- More analysis of data set and apps for interaction with the data
 - See poster from Lev Litichevsky and Ryan Peckner
- CRISPR/Cas9-based gene disruptions in multiple cell types
 - Already in progress
- Profiling of drug effects in ESC-derived neurons
 - The ESC system has inducible Cas9 which will allow for further manipulations
 - See poster from Jennie Young, Joel Blanchard, and Fatema Abdurrob
- Deeper mining of comprehensive MS data
 - See poster from Jarrett Egertson

Creating neurons for high-content proteomics assays

Passive differentiation via growth factor withdrawal (GFW)

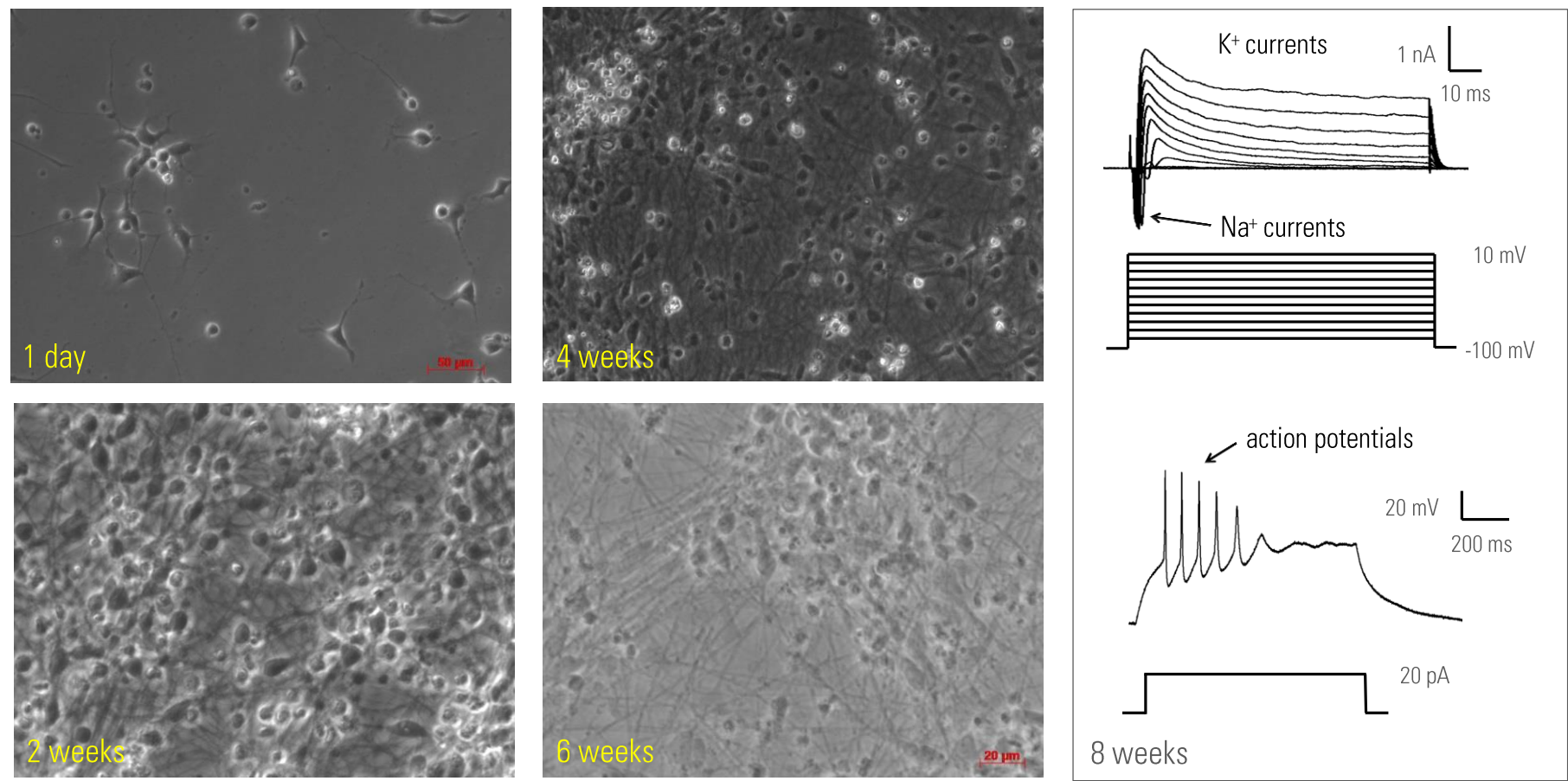


4 weeks

Proteomics and Biomarker Discovery

Creating neurons for high-content proteomics assays

Passive differentiation via growth factor withdrawal (GFW)

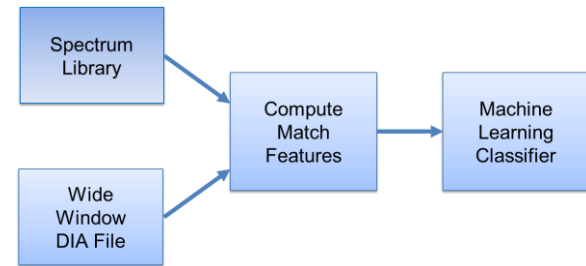


Next-gen comprehensive MS will extend the P100

- P100 data have been collected using a “DIA” MS method
 - Pioneered by MacCoss Lab
- DIA has the potential to identify and quantify 1000s of phosphosites in our data
- A key challenge is developing the algorithms to “unlock” these data

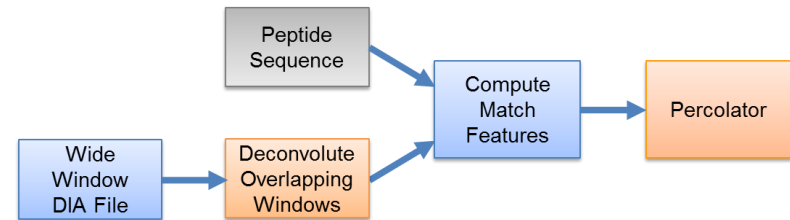
Two innovative tools for comprehensive MS analysis

■ Typical Workflow



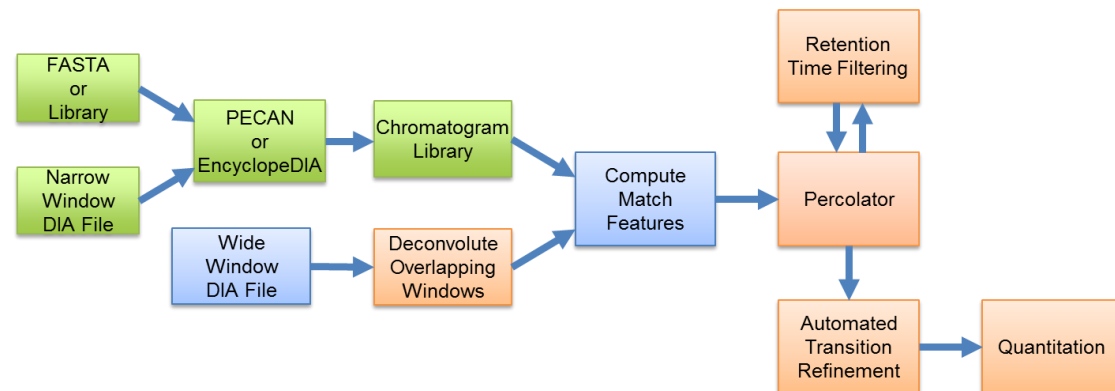
■ Tool 1: Pecan

- Uses only peptide sequences
- No spectral or retention time information

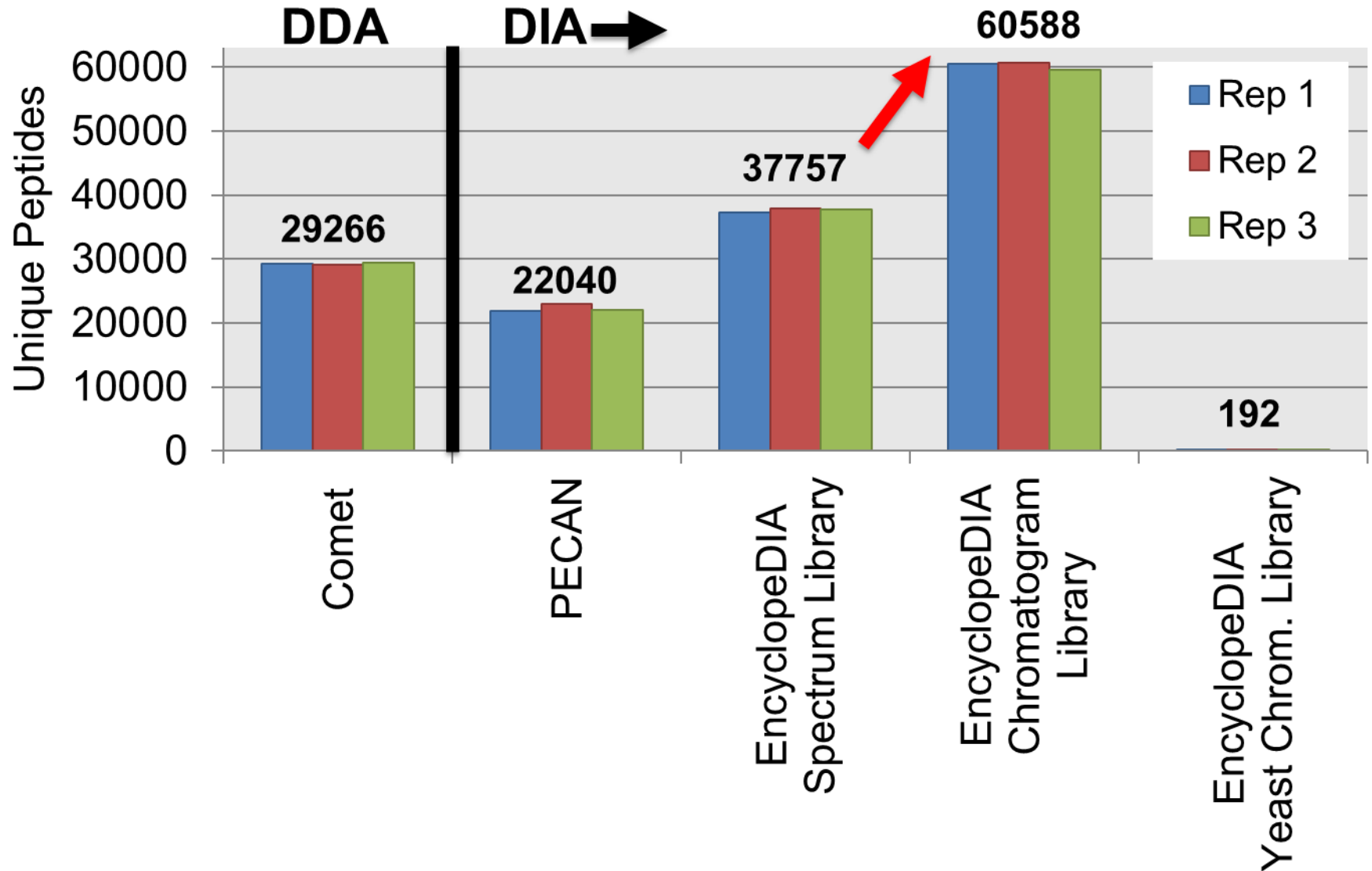


■ Tool 2: EncyclopeDIA

- Uses peptide sequences
- Spectrum or Chromatogram libraries
- Positional isomers



Pioneering methods meeting or exceeding goals

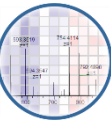


PCCSE Outreach and Intra-LINCS activities

- Signatures of cardiovascular hypertension induced by chemotherapeutic drugs
 - Molecular Cardiology Research Institute, Tufts Medical Center
 - See poster from Srila Gopal
- Signatures of neuropsychiatric phenotypes and their responses to drugs in patient-isolated iPS-derived NPCs and neurons
 - Massachusetts General Hospital
- Mapping of P100 probe-sets onto known pathway networks
 - Georgetown University and University of Delaware
 - Together with DCIC through LINCS EDSR
- Substrates to promote neuronal fates and phenotypes
 - Intra-LINCS with OHSU MEP LINCS Center

PCCSE Overall Summary

- Great progress has been made in the first two years in establishing our center
 - Vignettes illustrate the promise of our data
- Our neurobiology models are progressing nicely and we are excited to extend these further
- Next-Gen MS holds great promise for increasing the impact of our work
- We are poised to use our data “as is” for comprehensive connectivity analysis, but also as a springboard for comparison with new data to be made via:
 - Our continued efforts
 - Our outreach and collaboration efforts
 - Data made by third parties



Acknowledgments

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MIT – Tsai Lab & Stem Cell Core

Fatema Abdurrob
Tak Ko
Joel Blanchard
Jennie Young

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Sriha Gopal – Tufts Medical Center
Stephen Haggarty – Mass General Hospital

University of Washington – MacCoss Lab

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Brendan MacClean
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Ted Natoli
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Todd Golub