# SANOFI 57

Computational Systems Toxicology and in silico prediction of off-target activities. Case studies and discussion.



EUFEMED 2017, London, UK Friedemann Schmidt

# Outline

- Computational Systems Toxicology: Between data mining and mathematical modelling
- Advancing Confidence in Compounds and Prediction Tools. Application Examples.



# The main origin of toxicities



BIOLOGICS

# **Drug Off-Target Effects & Market Withdrawals**



## Safety Remains a Cause of Attrition



Project Termination, Sanofi 2000-2010





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### **Computational Toxicology**

- Drivers to improve current computational/systems toxicology capabilities
  - Low/no physical availability of substances
  - Cost of experiments
  - Speed / turnaround time
  - Reduction of (animal) experiments
  - Generating hypothesis for MoT  $\rightarrow$  design of in vitro and in vivo screening strategy



# Systems Toxicology is leveraged by a broad range of computational approaches



### **Toxicity = f(chemical structure)**

Toxicity =  $c_1 * descriptor_1 + ... + c_k * descriptor_k + c_0$ 

#### **Typical descriptors:**

- lipophilicity, H-bonding capacity,
- static or dynamic polar surfaces (PSA)
- free energy of solvation
- properties from ab initio calculations
- CoMFA, CoMSIA fields

# Goal: Correlate compound properties with interpretable molecular features (2D / 3D)



#### **Technology: Molecular Descriptors for Chemical Structures**

- Descriptors are provided by chemometrics software, such as DRAGON, MOE, PipelinePilot, MoKa, …
- Global descriptors
  - Atom & bond counts, indices
  - 1D descriptors
    - Molecular weight, physico-chemical properties
  - Diameter, dipole moment, pka, charge
- 2D descriptors
  - Fragments, pharmacophoric indices, topology

#### 3D descriptors

- volume, partial surface area,
- pharmacophoric features





#### **Example 1: Computational Phototoxicity Evaluation**



#### Liability assessment, calculation of probability of photosensitation

- Recursive partitioning classifier
  - Integrated UV absorption permeability, phototoxic fragments
  - Predicted property is the probability of positive in vitro test
  - Good statistical model parameters ROC<sub>test</sub> > 0.8







### **Adverse Polypharmacology:**

Toxic effects are often driven by off-target interaction



- The majority of adverse drug reactions are time and dose-dependent\*\*
- Adverse reactions often depend on the pharmacology profile of the candidate molecule





\*Mestres et al., DDT 14 (9), 479-485. \*\*Bowes et al., NRDD 11, 909-922, 2012.

# **Predicting Adverse Polypharmacology**

#### Experimental information

- Large target activity databases are available with millions of data points
- Screening collections with well annotated biological data are included in phenotypic screening sets (Deorphaning set)

#### CTlink (Chemotargets)

- Similarity and QSAR-based
- Multiple descriptors: PHRAG, FPD, SHED.
- Five statistical approaches for activity prediction.

Today 5818 target models from public data, 1811 Sanofi-models

#### Off-target QSAR models (predictProfile)

- Models are generated for off-target panels automatically
- Applicability domain defined by similarity to training set.
- Predictive models for 400 targets SAR sets.
- Reflecting Sanofi off-target profiling

D. Vidal, J. Mestres, Mol. Inf. 2010, 29, 543–551.

SANOFI J http://www.chemotargets.com/







# Example 2: Which molecular initiating events are causal for severe cardiotoxic effects of an antifungal lead compound?



#### **Example 2: Two distinct interactions putatively responsible**



- AchE: Airway obstruction, behavioural effects
- CHRM1: ventricular tachycardia, constriction of bronchia

Network representation: Compound interactions with muscarinic CHRM1 and acetylcholinesterase AchE are considered causal for the observed effects.



# Network enhancements using biomedical knowledge to model developmental toxicity



#### **Example 3: Off-target assessment for cardiosafety**



#### Multiscale Modelling suggests non-prohibitive APD shortening.

#### Simulation



#### Rabbit purkinje fiber

- Concentration-dependent decrease in action potential duration from 3 µmol/L
- Putatively consistent with an effect on Na+ and/or Ca++channels.
- Not suggestive of a proarrhythmic profile



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### **General Workflow**



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# Example 4: Comparative Genotoxicity assessment for Kinase Inhibitors

- Focal-adhesion Kinase FAK, Tie2 receptor tyrosine kinase and Kinase insert domain Receptor KDR are tyrosine kinases with implication in cellular proliferation and a decisive role in angiogenesis
- Protein kinases often share a significant similarity of the binding pocket, thus Polypharmacology is often observed, and selectivity is difficult to achieve





# Example 4: Comparative Genotoxicity assessment for Kinase Inhibitors

- Assumption: Side effects are driven by specific compound features
- Model-assisted assessment of Kinase selectivity:



### Example 5: AE prediction of a FAAH Inhibitor

#### • Fatty-acid-amide-hydrolase (FAAH serine hydrolase) inhibitor

- FAAH is mediator in the endocannabinoid system
- Potentially (partially?) irreversible mode of action
- Low potency in rodents: (IC<sub>50</sub><sup>rat</sup>=1.1 μM)
- Significant metabolism
  - Unknown level of metabolite
- No apparent reactivity
- Compound specificity
  - Selectivity of compound and metabolites
  - Serine hydrolases: monoacylglycerol lipase (MAGL), a carboxyl esterase and acetylcholinesterase (10 fold selectivity for FAAH rat, 50 fold for FAAH human).

BIA-102474

- 100 fold against dopamine-beta-hydroxylase, glutamic acid decarboxylase, the monoamine oxidases A and B and choline acetyl transferase.
- Other inhibitors have higher selectivity margins (e.g. PF 04457845 Pfizer )
  - Disproportionate PK may lead to tissue exposure exceeding the margin



M1

M2

#### Supporting Risk Assessment by Off-target Prediction

- CTlink off-target assessment may be used to suggest potentially unexplored interactions of the substance and/or metabolites with endocannabinoid system
  - Refine in vitro safety screening strategy to include predicted targets (starting with predictions having a high confidence factor)



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### Supporting Risk Assessment by Off-target Prediction

- CNS predicted as potential target organ
- Support for hypothesis generation, e.g. interactions with the endocannabinoid system could contribute to adverse effects at high tissue exposure.

<i>⊊}+€7+€</i> +€ BIA.10-2474.new		Bra	in injuries
Neighbours sharing h	azards		
Distinctive hazards			
Targets			
Number of targets	Contribution	Maximum EF	Average EF
1	63.48%	1.95	1.95
Translocator prote	in		P30536 🛃
Pathways			
Fragments			

			NeuroTox 12							
	Identifier	Main term	Category 1 A	I	M	Confidence 2 v	pAct			
r	M2	Cns disorder	NeuroTox	Ρ		0.55	6.0			
3	BIA.10-2474	Headache	NeuroTox	Ρ		0.53	6.0			
3	BIA.10-2474	Nervous system disorder	NeuroTox	Ρ		0.53	6.0			
3	M2	Nervous system disorder	NeuroTox	Ρ		0.52	6.0			
3	M2	Headache	NeuroTox	Ρ		0.51	6.0			
3	BIA.10-2474	Spinal diseases	NeuroTox	Ρ		0.48	6.0			
r	BIA.10-2474	Brain injuries	NeuroTox	Ρ		0.34	6.0			
3	M2	Neuropathy	NeuroTox	Ρ		0.33	6.0			
3	BIA.10-2474	Encephalopathies	NeuroTox	Ρ		0.32	6.0			
3	M1	Cns disorder	NeuroTox	Ρ		0.30	<b>7</b> .0			
3	BIA.10-2474	Cns disorder	NeuroTox	Ρ		0.30	<b>7</b> .0			

SUMMARY S-links 69 0 Known Predicted 69 7.0 Max affinity 6.0 Min affinity Max confidence 0.55 Min confidence 0.30 By safety category 3 CardioTox EndocrinoTox 1 EyeTox 2

# **Example 6: FFAR1 Agonist Fasiglifam**



- Potent orally available, selective partial agonist of human FFAR1
  - Advanced for type 2 diabetes before stopped in Phase III clinical development
  - Once daily oral administration to type 2 diabetic patients for 24 weeks was well tolerated and led to reduced HbA1c levels and reduction of fasting plasma glucose.
  - A slightly higher incidence of 3-fold elevated alanine transaminase (ALT) in the fasiglifam compared to placebo groups was observed. Although a majority of patients with elevation of aminotransferases had confounding factors, in some cases, drug-induced liver injury couldn't be excluded completely leading to a termination.



# **Slink Systems Toxicology Analysis**

Identifier			Mainte	rm		Alert type			Co	Х	(		
00000001		Precli	nical hepatot	oxicity findings		Preclinical			0.53			6	
☆ 00000001	00000001 Mitotoxicity		•	Preclinical			0.62	#1	1				
pACT(P)	Effe	ct	Methods	Confidence score 1	•	Target name							
<b>7</b> .4	AGO[K]		000001	0.85	Free fatty acid receptor 1			ig mis.					
6.4	Peroxisome proliferator-activated rece		d recept	tor alpl	na	201							
<mark>=</mark> 5.9			001100	0.77	Per	oxisome proliferator-activated	ome proliferator-activated receptor delta		a				
<b>A</b>				0.38	Bile	acid receptor						- Developing the sect	
<mark>=</mark> A				0.37	Prostacyclin receptor			0000001		Preclinical hepat			
A 🗧				0.37	Lys	ophosphatidic acid receptor 3	3						
<mark>=</mark> A				0.37	Cys	teinyl leukotriene receptor 1				Drug neighbours			
<b>A</b>				0.37	Leu	kotriene B4 receptor 2				Number of neighbours		Contribution	
<b>A</b>				0.34	Gly	cogen [starch] synthase, muse	cle			9		76.77%	
Liver predicted as target organ						Drug name		Neighbouring criteria					
Matak		0.04	huova	mradiata	d.					furosemide	Ľ	Similar hazards (3)	
	DOIIC Detivo	pat	nways		<b>a:</b>					chlorpromazine	Ľ	Similar hazards (3)	
Gluci	ironia	tatio	n							fenofibrate		Similar hazards (3)	
Hydroxylation Dehydrogenation							Levothyroxine		Similar hazards (3)				
<ul> <li>Sulfatation</li> </ul>							HT0943		Similar hazards (3)				
			_							HT0273	Ľ	Similar hazards (3)	
Putative interactions							montelukast	Ľ	Similar hazards (3)				
• FFAR	k1, Pl	PAR	a/d,, bile	e acid recep	tor	BSEP				telmisartan		Similar hazards (3)	

# Metabolic Pathways

Abundant pathways in hepatocytes of human, dog and rat



Formation of TAK875-GlcA:

HEP: 13% HEP: 2-4% HEP: <LOD





• In vitro metabolism of human dog and rat

Human

Dog

Rat

- low (< 20%) in hepatocytes of all species,
- low (< 20%) in liver microsomes with NADPH in all species,
- moderate (38-62%) in human and dog liver microsomes with UDPGA
- O-Acyl-glucuronide in hepatocytes is disproportionate in human
- The rate of disappearance (t<sub>1/2</sub>) of the 1-O-acyl-glucuronide of was 2.6 h, clearly below the reference compound furosemide-O-acyl-glucuronide with 3.8 h, indicating a potential risk of reactivity.



# In vitro Assessment

#### Cytotoxicity in primary human hepatocytes /GSH depleted hepatocytes

- No biologically significant difference in the cytotoxicity
- No alteration of the total GSH decrease in total GSH content at non-toxic concentration

#### Mitochondrial Toxicity

 Effects on human mitochondria and cellular metabolism do not appear to be the primary mechanism of cytotoxicity following 4hr exposure of human hepatocytes.

#### Transporter engagement



	Fasiglifam	Fasiglifam-Glca
Passive permeability	high	Very low
Uptake	Passive	active
OATP1B1	inhibitor	Inhibitor/substrate
OATP1B3	inhibitor	inhibitor
MRP2	-	Inhibitor/substrate
BSEP	inhibitor	-



# **Reactive Metabolites**

- No significant covalent binding in liver microsomes of all species.
- In human hepatocytes a slight increase of covalent binding compared to the animal species.
- The slight potential of covalent binding confirmed in liver microsomes of human and dog after addition of UDPGA in 6h
- O-acyl-glucuronide metabolites solely suspected for covalent binding potential, as their abundancies were far below 5% in animal hepatocytes and the other human metabolites were observed at least in one *in-vitro* animal species with similar or higher abundances, as seen in human hepatocytes

Mean drug related material recovered in pellet <sup>1</sup> , given in [pmol eq./mg protein]												
Cofactors/ Species	-NADPH	+NADPH	+NADPH +GSH	-NADPH +UDPGA	+NADPH +UDPGA	-NADPH	+NADPH	-NADPH +UDPGA	+NADPH +UDPGA	HEPs	HEPs	HEPs
Incubation	1h	1h	1h	2h	2h	6h	6h	6h	6h	2h	4h	6h
Number of replicates	1	1	1	7	7	3	3	7	7	3	3	5
Rat M	0	0	0	nd <sup>2</sup>	nd	nd	nd	nd	nd	nd	2	nd
Dog M	12	13	2	14	12	8	9	23	21	5	8	10
Human M/F	5	1	0	12	15	11	15	27	26	46	99	84

1: after repeated wash steps with methanol/sulphuric acid solution and solubilizing with Solvable<sup>™</sup>, corrected with 0h results

2: nd: not determined

HEPs: hepatocytes; M: Male; F: Female; M/F: Pool of male and female subject



# Summary

- Computational systems toxicology
  - Tailored databases, prescriptive and predictive methods to improve compound safety
- Computational profiling complements and supports in vitro/in vivo screening strategy
  - QSPR/QSAR is an extensible technology for various predictive models
  - Cost-effective tools to select compounds and plan experiments early
  - Better planning and more focused design of mechanistic studies (in vitro/in vivo) to explore MoT
  - Risk mitigation
- Regulatory acceptance is increasing
  - e.g. ICH M7: no further investigations if in silico models + expert knowledge conclude negative result

Toxicological in-silico analyses aim for a significant reduction in potential risks resulting from unforeseen drug adverse events in all phases of drug discovery and development

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