# How networks could be useful? Simulation-first drug discovery in oncology

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# 1. Who are we?

Why do we need Turbine?
 Overview of the technology
 Simulation benefit in drug discovery
 Summary and outlook

## Turbine | a snapshot

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#### Proprietary technology taking precision oncology beyond CRISPR



#### Simulated Cell™

- Cell behaviour simulation technology tackling high unmet need with the potential of enhanced clinical success
- Focus on oncology
- Patent-protected
- Based on 10+ years of research

Building pipeline targeting massive unmet oncology need for 1.5 years

targets<br/>tackling PARPi<br/>resistance2 Hit finding phase1 Initial patent filed

**Predictions validated in clinical trials** 



5 of our predictions are investigated in Phase 1 – 3 clinical trials



**Backed by tech/life sciences VCs** 

- AI Engineers
- Data scientists
- Software developers
- Molecular & translational biologists
- Medchem experts



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# Advancements in molecular diagnostics leads to the fragmentation of cancer indications

Histological subtypes	Ductal	Lobular	Molecular subtypes	Triple negative ER-, PR-, HER2-	HER2+	Luminal B	Luminal A
Preinvasive cancer 25% Cells limited to	Ductal carcinoma in situ (DCIS) 80% May soread through ducts	Lobular carcinoma in situ (LCIS) 20% Does not distort duct	% of breast cancers	15-20%	10-15%	20%	40%
pasement membrane	and distort duct architecture 1% progress to invasive cancer per year Usually unilateral	architecture Same genetic abnormality as ILC – E-cahderin loss 1% progress per year Can be bilateral	Receptor expression		HER2		ER+/PR+
			Histologic grade	High (grade III)		All and the second	Low (grada I)
Invasive cancer <sup>75%</sup>	Invasive ductal carcinoma (IDC) 79%	Invasive lobular carcinoma (ILC) 10%	Level of cell differentiation				Low (grade I)
Extension beyond the basement membrane	Usually from DCIS precursor Cause fibrous response, producing a palpable mass on examination	Usually from LCIS precursor Minimal fibrous response, presents less often with palpable mass	Prognosis Correlates to histologic grade	Poor			Good
	Metastasis through lymphatics and blood	Metastasis through abdominal viscera to GI, ovaries, uterus Almost always ER+	Response to medical therapy	Chemotherapy	Trastuzuma	b	Endocrine
urr Treat Options Oncol. 2000 Iin Transl Oncol. 2008 Dec;10	Aug;1(3):199-209. Nat Clin Prac (12):777-85. Robbins 8E	t Oncol. 2007 Sep;4(9):516-25.		Triple negative tumours respond bes chemotherapy, similar to other aggre		Luminal A tumours	respond best to endocrine rogen or aromatase inhibitor.

# Advancements in molecular diagnostics leads to the fragmentation of cancer indications



"355 and 195 TNBC samples from the Molecular Taxonomy of Breast Cancer International Consortium (METABRIC) and The Cancer Genome Atlas Consortium (TCGA)". "We were able to globally reproduce Lehmann's TNBC classification with BL1, IM, LAR, M and MSL being the more stable subtypes"

<sup>6</sup> Y Bareche et al. (2018) Unravelling triple-negative breast cancer molecular heterogeneity using an integrative multiomic analysis, *Annals of Oncology*, 29, 4:895–902

## **Resolution of companion diagnostics** getting more and more precise

Oncotype Dx RS : 16(+5)

#### Foundation One : 315+28



#### FOUNDATIONONE® CURRENT GENE LIST

FoundationOne\* is a pan-cancer comprehensive genomic profile, which interrogates the entire coding sequence of 315 cancer-related genes plus introns from 28 genes often rearranged or altered in cancer.

URRENT GE									
ABL1	BRAF	CHEKI	FANCE	GATAS	JAK2	MITE	PDCDILG2	REMIO	STAT4
ABL2	BRCAI	CHEK2	FANCD2	GATA4	JAKS	MLHI	PDGFRA	RET	STIKT
ACVRIB	BRCA2	CIC	FANCE	GATAS	JUN	MPL	PDGFRB	RICTOR	SUFU
AKTI	BRD4	CREBBP	FANCE	GID4 (C17orf39)	(MYST3)	MREIIA	PDK1	RNF43	SYK
AKT2	BRIP1	CRKL	FANCG	GLI	KDMSA	MSH2	PIK3C28	ROS1	TAFI
AKTS	BTGI	CRLF2	FANCL	GNATI	KDMSC	MSHG	PIKSCA	RPTOR	TBX3
ALK	втк	CSFIR	FAS	GNA15	KDM6A	MTOR	PIKSCE	RUNX1	TERC
AMERI FAMI258)	Cliorf30 (EMSY)	CTCF	FATI	GNAG	KDR	MUTYH	PIKSCG	RUNKITI	TERT (promoter o
APC	CARD11	CTNNAI	FBXW7	GNAS	KEAPI	MVC	PIK3RI	SDHA	TET2
AR	CBFB	CTNNBI	FGF10	GPR124	KEL	MYCL (MYCL1)	PIKSR2	SDHB	TGFBR
ARAF	CBL	CULS	FGF14	GRIN2A	KIT	MYCN	PLCG2	SDHC	TNEAIP
ARFRP1	CCND1	CYLD	FGF19	GRMS	KLHL6	MYDEE	PM52	SDHD	TNERSE
ARIDIA	CCND2	DAXX	FGF23	GSKSB	KHT2A (MLL)	NF1	POLDI	SETD2	TOPI
ARIDIB	CONDS	DDR2	FGF3	H3F3A	KMT2C (MLL3)	NF2	POLE	SF381	TOP2A
ARID2	CONET	DICERI	FGF4	HGF	KMT2D (MLL2)	NFE2L2	PPP2R1A	SLIT2	TP53
AS01.1	CD274	DNMT3A	FGF6	HNFIA	KRAS	NEKBIA	PRDMI	SMAD2	TSCI
ATM	CD79A	DOTIL	FGERI	HRAS	LMOT	NIO(2-1	PREX2	SMADS	TSC2
ATR	CD798	EGFR	FGFR2	HSD3B1	LRPID	NOTCHI	PRKARIA	SMAD4	TSHR
ATRX	CDC75	EP300	FGFR3	HSP90AA1	LYN	NOTCH2	PRICI	SMARCA4	U2AF1
AURKA	CDHI	EPHA3	FGFR4	IDH1	LZTRI	NOTCHS	PRKDC	SMARCE1	VEGFA
AURKE	CDK12	EPHAS	FH	IDH2	MAGI2	NPM1	PRSSB	SMO	VHL
AXINI	CDK4	EPHA7	FLCN	IGFIR	MAP2KI	NRAS	РТСНІ	SNCAIP	WISP3
AXL	CDK6	EPHEI	FLTI	IGF2	MAP2H2	NSD1	PTEN	SOCSI	WTI
BAPI	CDKB	ERB82	FLTS	KEKE	MAP2K4	NTRKI	PTPNII	SOKIO	XPO1
BARDI	CDKNIA	ERB83	FLT4	IKZF1	марзкі	NTRK2	GKI	SOX2	ZBTB2
BCL2	CDHNIB	ER884	FGKL2	L7R	MCL1	NTRKS	RACI	SOX9	ZNF217
BCL2L1	CDKN2A	ERG	FOXP1	INHEA	MDM2	NUP93	RADSO	SPEN	ZNF703
BCL2L2	CDKN28	ERREN	FRS2	INPP48	NDH4	PAKS	RADSI	SPOP	
BCL6	CDHN2C	ESRI	FUEPI	IRF2	MED12	PALE2	RAF1	SPTAL	
BCOR	CEBPA	EZH2	GABRAS	IRF4	MEF28	PARK2	RANBP2	SRC	
BCORLI	CHD2	FAM46C	GATA1	IR52	MENT	PAXS	RARA	STAG2	
BLM	CHD4	FANCA	GATA2	DAK	MET	PERM1	RBI	STATS	
ELECT REAR	RANGEMENT	5							
ALK	BRAF	BRD4	ETV4	FGFRI	KIT	HVC	NTRK2	RARA	TMPRSS
BCL2	BRCAI	EGFR	ETVS	FGFR2	MSH2	NOTCH2	PDGFRA	RET	
BCR	BRCA2	ETVI	ETV6	FGFRS	HVB	NTRKI	RAF1	ROSI	

\*Current as of August 18th, 2014.

The analytic validation of PoundationOne", based on a price reveales of the PoundationOne" havang (28 genes, 18 obied memorgements), was published in Nature Biotechnology<sup>6</sup> and established the performance specifications required to deve the high heart of accuracy motively obtained by Discontrol Control on the second generic attention. This spatiation of PoundationOne" and these performance sees Plastices is demonstrating to the concentron ends performance performance and performance and performance and the set of the sublished version of PoundationOne" and the performance and Plastices is demonstrating to the concentron ends performance public of the Concol development of the validated areas of period according on the concentration to the concentration ends on the sublished version of PoundationOne".

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## **Examples for indication-agnostic targeted therapy**



# Understanding cancer complexity on a scalable way opens markets but poses challenges to pharma R&D

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As we understand biology better, new segments are opening for novel treatments



Key gaps filled by understanding underlying biology



Relevant target

First patient to dose



Patient response



Overcoming resistance

# Better understanding of biology Note: Sector of the secto

# More clinical approvals with higher success rate

## **Concept of Turbine**

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Integration of biological knowledge into a mechanistic model



Understand behavior of tumors with simulations and predict outcome



Identify responder and non-responder patient populations much earlier during the preclinical phase



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# Better understanding of genotype-phenotype relations by signaling modeling

Current solutions are correlating genotype with phenotype



Turbine is looking for the hidden features connecting the two layers of complexity 公



## Three main pillars of the technology



Simulated Cell model



Modelling of phenotypic behavior

Interpretation by biologists guided by AI

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## **Molecular layers of the Simulated Cell model**

### Wiring diagram

#### => signaling network

Manually curated, primarily protein-protein interaction based signaling network with 2500+ nodes and 6200+ interactions.

#### Genomics

#### => protein activity & function

Example: KRAS gene damaging mutation makes the protein constitutively active, while a similar falteration in the P53 gene causes loss-of-function

## Transcriptomics

#### => est. protein concentration Example: EGFR receptor

overexpression increases its concentration in the model

## Compound library

#### => inhibitory/activatory effect

Example: by knowing the targets of a receptor tyrosine kinase (RTK) inhibitor, we can inhibit them according to their binding affinities

## Main signaling pathways covered by the model



#### AMPK 1)

- Apoptosis 2)
- B-cell receptor 3)
- Calcium signaling 4)
- 5) DNA damage response
- 6) ER stress
- 7) ErbB
- G-proteins 8)
- Hedgehog 9)
- 10) Hippo
- 11) Hypoxia
- 12) T-cell receptor signaling
- 13) NFKB
- 14) JAK/STAT
- 15) MAPK



17) NFKB 18) Notch 19) p38/JNK 22) Proliferation 23) Proteastasis/Akt/mTOR/ 24) RTK signaling 25) Steroid signaling 26) TGFB 27) Toll-like receptor signaling 28) VEGF 29) WNT

## Modelling of phenotypic behavior



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### **Three steps of validation**

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## Interpretation by biologists and AI



## We've built our patent-protected Simulated Cell platform to understand biology early and at scale

#### Key features of the Simulated Cell

#### **Model building**

- Manually curated general network
- Based on molecular biology literature, trained on proprietary *in vitro* data
- 2.500+ nodes in 23 signaling pathways
- 6.000+ interactions

#### **Already modeled**

- 200+ patients' data
- 611 cell lines
- 185 drugs in monotherapy and combinations





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# Turbine's predictions have changed the fate of several projects with BAYER and other collaborators

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# Uncovering indication expansion opportunities for a potential blockbuster drug for Bayer (clinical trial running)

Because Bayer was interested in expanding the potential uses of one of their drugs, they approached us for help in discovering new indications.

#### Expanding the indications

- Bayer wanted to expand its drug either across a greater number of patients (vertically), or over time (horizontally).
- The solution to both was to discover potential drug combination partners.
- Our *in silico* screening delivered **21 combination predictions**, of which **13 were validated** *in vitro*.

#### <u>Outcome</u>

Of the 13 validated predictions, Bayer has chosen one that is currently being investigated in a Phase II clinical trial.



# Escapes routes of cancer – ways to develop resistance, blocked by combination therapies



# Identifying a new patient selection biomarker for Bayer's inhibitor beyond a known marker

For this collaboration, our partner needed a novel biomarker in order to stratify patients for its compound. However, standard bioinformatics methods couldn't identify anything beyond a known marker

#### The process

- To identify the novel biomarkers, we needed a high molecular diversity of (simulated) cells that were not otherwise covered by available cell lines.
- Turbine identified several biomarkers, just as strong as – if not stronger than – the known marker.
- After further experiments, we have selected 5 sensitivity and 2 resistance biomarkers.

#### <u>Outcome</u>

As a result of our work, our predictions were able to guide the Phase II clinical trial planning



#### Effect strength distribution of highlighted biomarker hypotheses

## Network strategy to find non-trivial biomarkers



# Uncovering novel patient sensitivity signatures while modeling resistance in blood cancer patient cells



While collaborating with a hematology research group, we were tasked with understanding why certain targeted therapies worked for specific Chronic Lymphocytic Leukemia (CLL) patients, while others would respond to another targeted therapy.

Understanding the disease mechanism

- Our investigation began with approx. 200 patients' mutational and clinical data.
- Simulated Cell<sup>™</sup> leveraged the breadth of its dataset to help analyze and predict rates of acquired resistance and success rates for targeted therapies.

#### <u>Outcomes</u>

- Our predictions showed a high occurrence of acquired resistance against ibrutinib among PI3K- and BTK- mutated patients
- We were able to identify that gene signatures are more crucial than any single gene biomarker.



Analysis of *simulated* molecular alterations leading to resistance

# Turbine advantages in finding novel cancer targets compared to CRISPR

CRISPR overlooks several mechanisms driving cell behaviour and the evolutionary pressures leading to resistance. In comparison, the Simulated Cell™ takes a holistic view of the cell and deploys cell behaviour simulations to quickly reveal the potential of the targets' clinical relevance.

1.	Precision	<b>CRISPR Limitations</b>	Drug Discovery (Dis)Advantage	Turbine Advantage	Turbine Proof	
	Targeting	Knocks out the entire gene	Pharmacological inhibitors may have different phenotypic effect, gene product may be undruggable	Simulate partial inhibition functional KO to reveal viable targets, identify alternative, druggable targets with similar phenotypic effect	We identified ATR as a promising target, as opposed to DepMap which considers it toxic due to its common essentiality	
		Does not yield mechanistic insight	Biomarkers for patient stratification may not be identified	Biomarkers can be identified based on mechanistic understanding	We identified ATM LoF as a sensitivity biomarker for ATRi, currently in Phase 2 validation	
2.	Durability					
		Limited to one gene KO at a time	Tumor may escape through alternative pathway, genetic redundancies may be missed, combination approaches are hard to ID	Combined inhibition of several targets in tandem	We discovered and patented TURB1, a novel target tackling NHEJ-deficinecy driven resistance to PARPi	
3.	Translatability					
28		Limited to models which grow in 2D/3D cultures	Available models do not represent patient heterogeneity in many indications	Create cell models from any available sequenced tumor data	We predict clinically validated biomarkers for CLL, a blood cancer for which only a handful of preclinical models are available	

# Relying on the Simulated Cell™ platform, we turn preclinical research into clinical success



IND ready, first-

in-class asset with patient

stratification

biomarkers and

combination

strategy

Identify

unmet

resistance

need

# Continuous development of the Simulated Cell enables novel target screens, leading to the expansion of our pipeline





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# Unlike other computational platforms, we use one model to guide the entire R&D process by deep biological understanding

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## So where are we heading?

#### **Conclusions:**

- Deeper biological understanding is key to decrease biological uncertainty
- **Computational modelling based on network biology** is already helping drug discovery, leading to a **more efficient and rational process**, with feasible economics -> decreases time to the clinic, increases success rates

#### **Current trends:**

- Indication agnostic therapies
- Targeted therapies for given molecularly defined patient subgroups
- Increased importance of molecular diagnostics
- In silico decision support both in trials and in the clinic

## Véleményezés QR-kód-AOK



report.semmelweis.hu/pin PIN-kód AOK: KZ3 Véleményezés QR-kód-FOK



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