Artificial intelligence in personalized medicine

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Overview

(1) Introduction: Artificial Intelligence vs. Classical Statistics

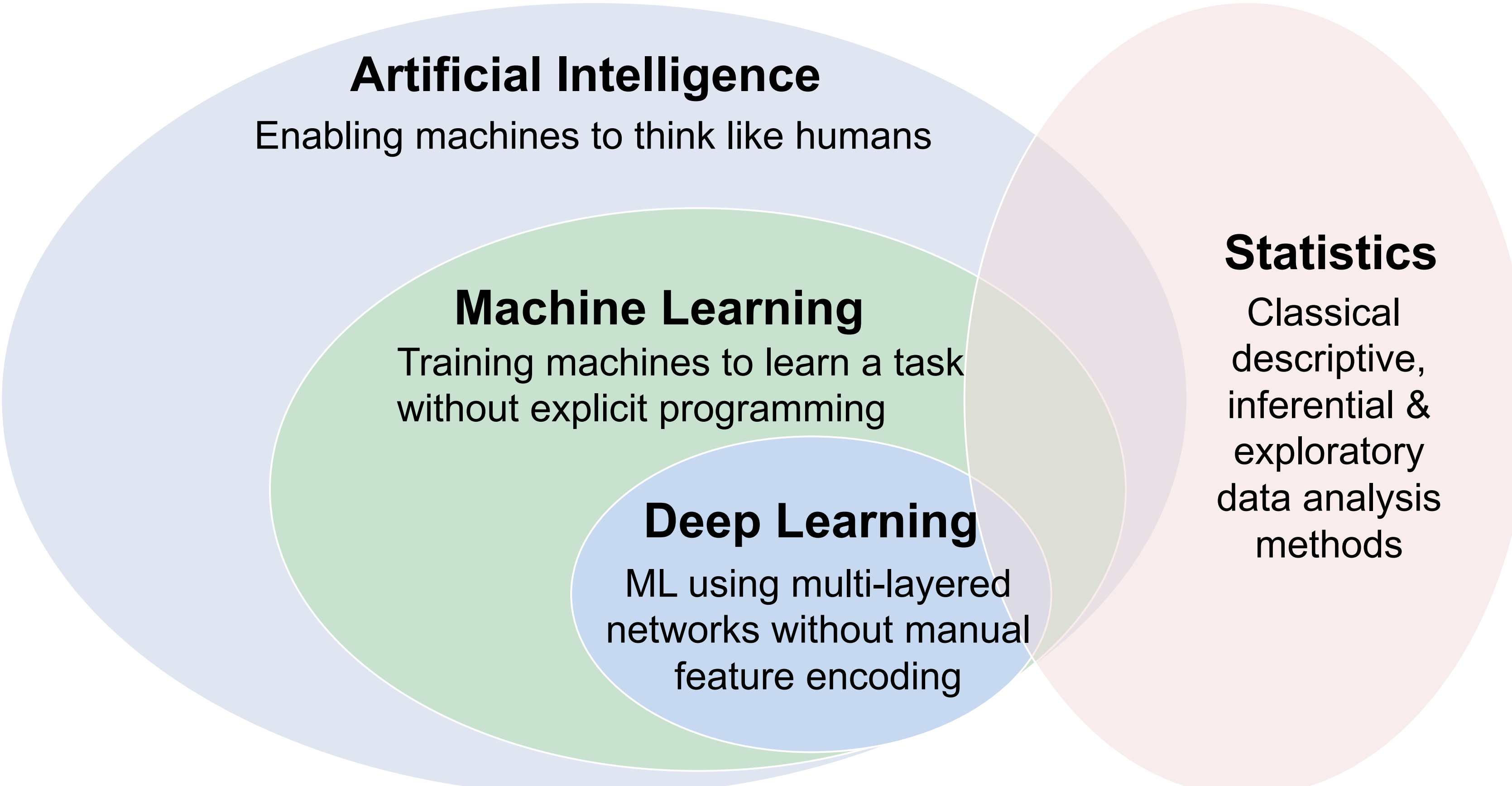
(2) AI success stories in recent years

(3) AI in personalized medicine:
- Biomarker discovery
- Drug discovery
- Digital health monitoring

(4) Common pitfalls and challenges

(5) Outlook on new AI strategies to address the challenges

AI vs. Statistics



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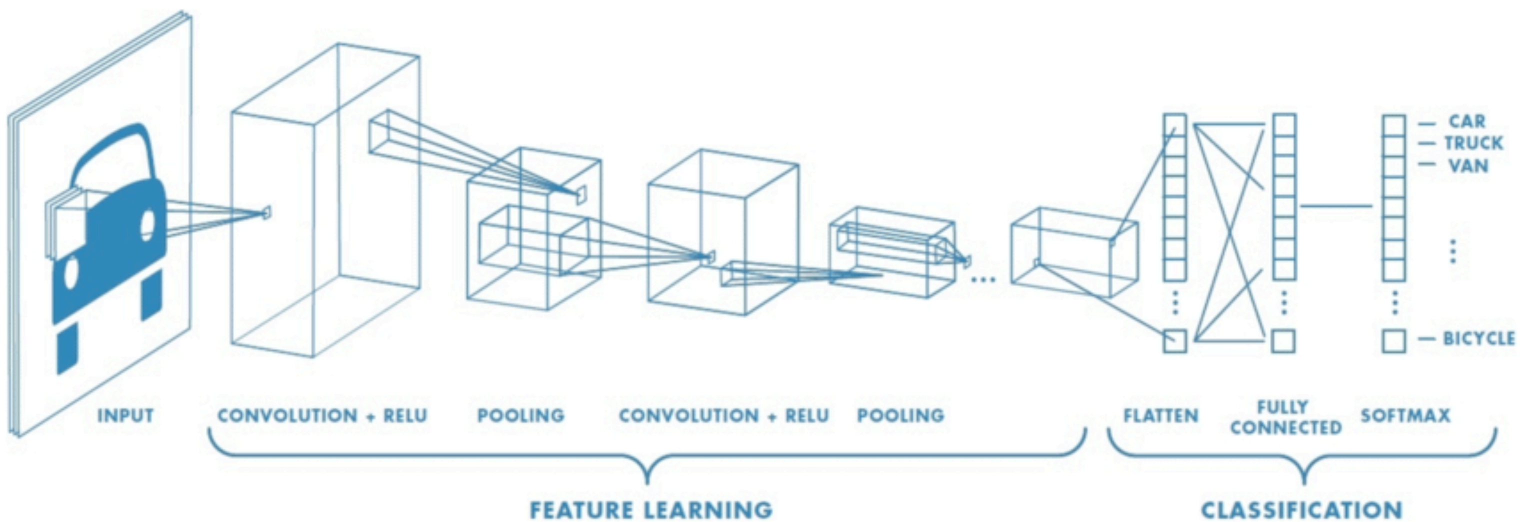
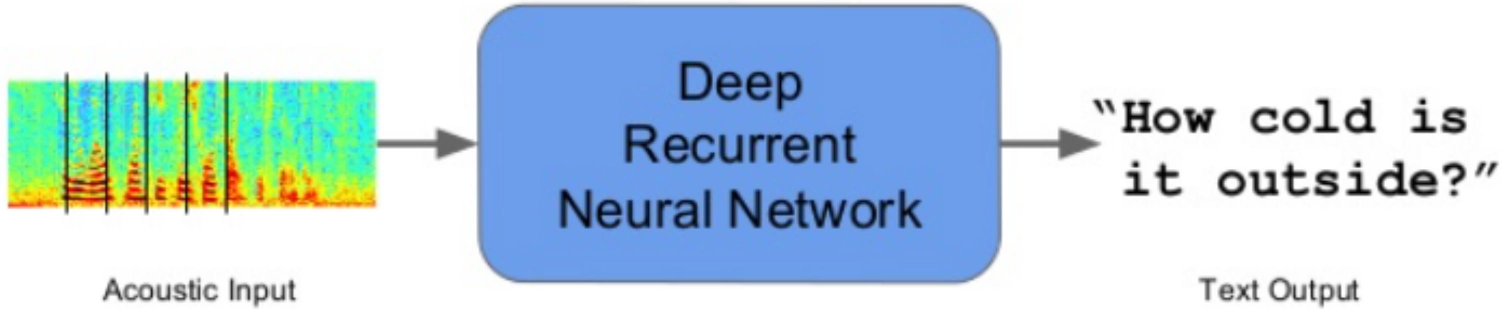
AI success stories: Image data (1)

- **Image classification**: unprecedented accuracies using deep learning (e.g. “AlexNet” approach by Krizevsky et al., 2012)
- **Novel techniques**: Convolutional Nets / Transformers, Dropout, Data Augmentation, Rectifier Nonlinearity, Local Response Normalization



AI success stories: Sequential data (2)

- **Speech recognition**: 30% less errors with new neural networks (Huang et al., ACM Communications, 2012)
- **Novel techniques**: Recurrent Neural Networks (RNNs): Long-Short-Term Memory Networks (LSTMs), Gated Recurrent Units (GRU), etc.



AI successes in personalized medicine - Biomarkers

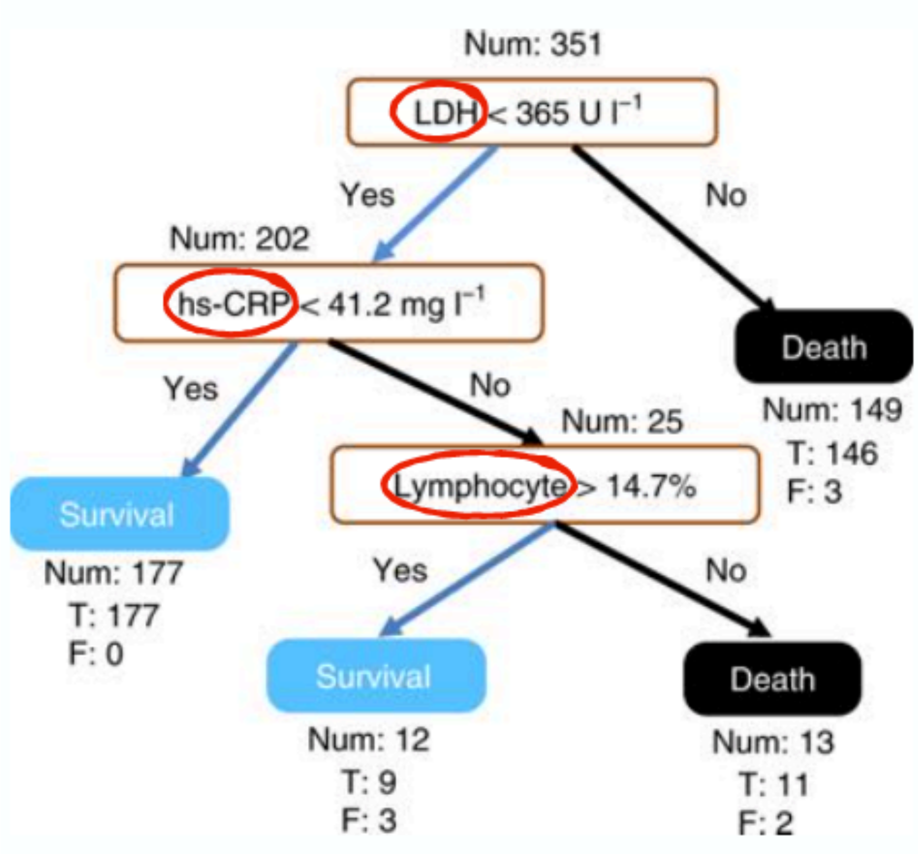
Multiple omics-based AI diagnostic tools already clinically validated:

Name	Test approval (FDA-cleared and/or LDT)	Purpose	References
MammaPrint	FDA-cleared, LDT	breast cancer risk-of-recurrence assessment	Van't Veer et al., Nature, 2002
AlloMap Heart	FDA-cleared, LDT	identifying heart transplant recipients with risk of cellular rejection	Yamani et al., J Heart Lung Transplant, 2007
Prosigna Assay / PAM50	FDA-cleared, LDT	breast cancer risk of distant recurrence prediction	Nielsen et al., BMC Cancer, 2014
Oncotype DX	LDT	breast cancer risk-of-recurrence assessment	Kelley et al., Cancer, 2010
Decipher	LDT	prostate cancer metastatic risk prediction	Marrone et al., PLoS Curr., 2015

AI in biomedicine: Covid-19 hospital mortality prediction

- Covid-19: alterations in common clinical blood tests when diagnosed

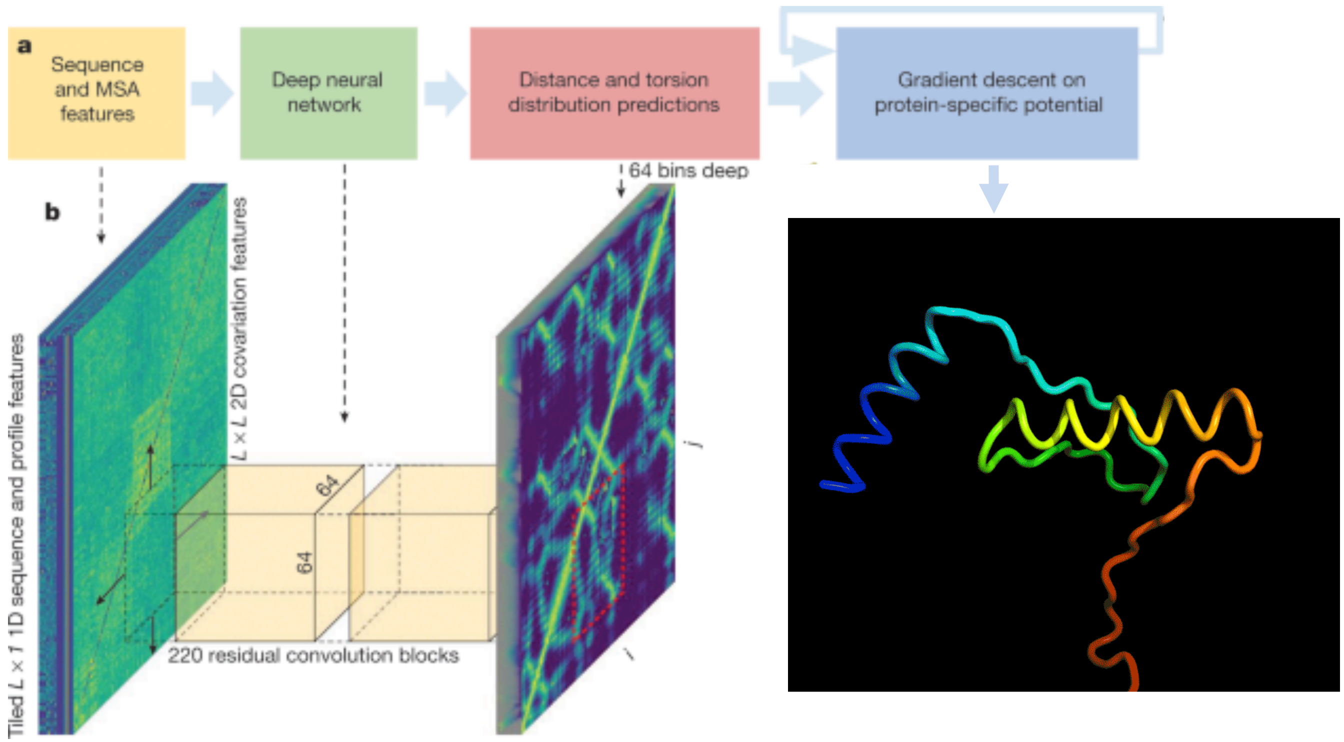
- Apply ML → 90% accurate predictions of mortality on test set of 110 patients (10 days in advance)



(source: Yan et al., Nat. Mach. Intell. 2, 2020)

Deep learning for biomedical research: AlphaFold 2

- DeepMind's AlphaFold 2 → major advance in protein structure prediction
- Scores > 90 in global distance test (GDT) in the CASP competition



(AlphaFold basic architecture; source: Senior et al., Nature 577, 2020)

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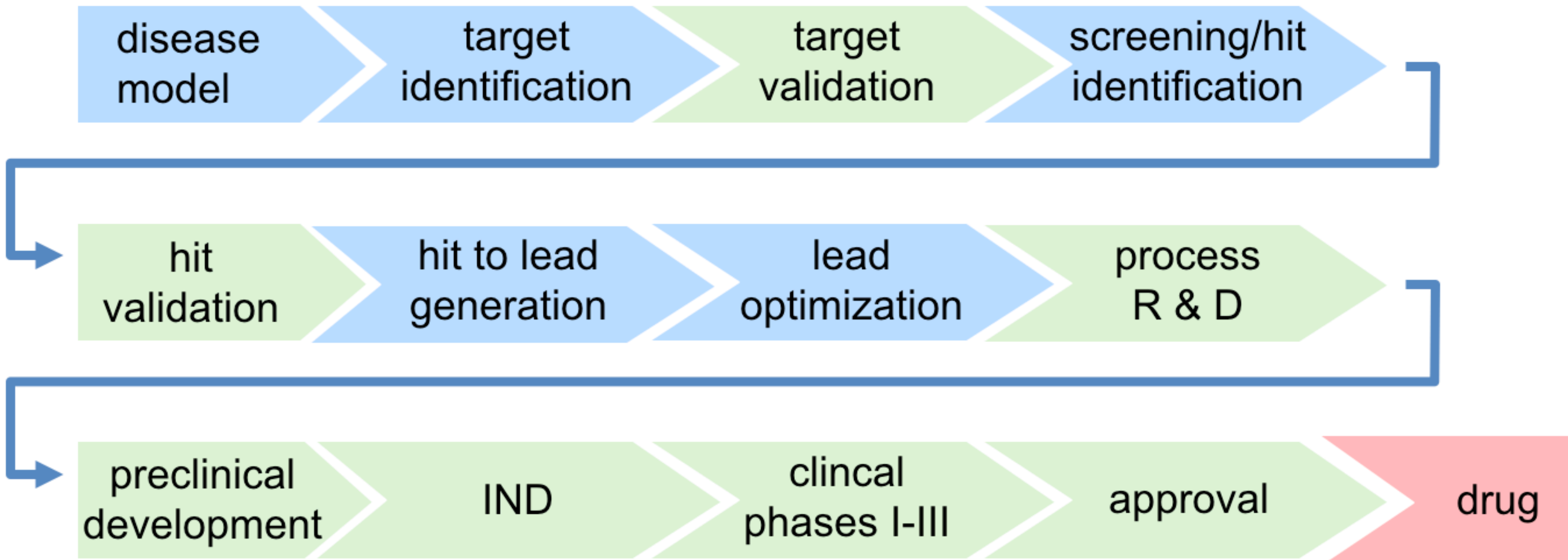
AI in drug development

Common phases in drug development:



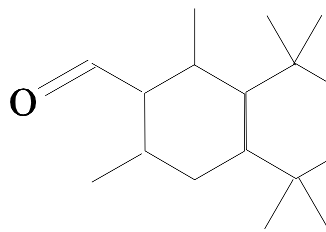
Opportunities for AI approaches highlighted in blue ( )

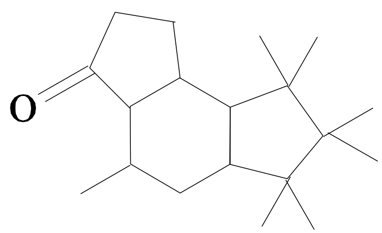
AI in drug development

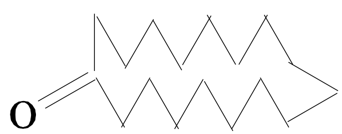
- **Question**: Which drug-like compounds bind to a particular target protein?

- **Example**: Active compounds Inactive / low activity compounds

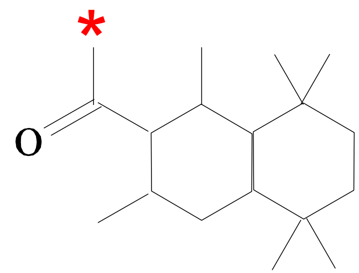
Active compounds

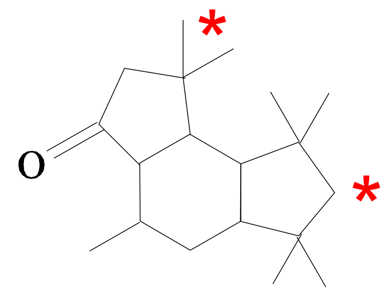






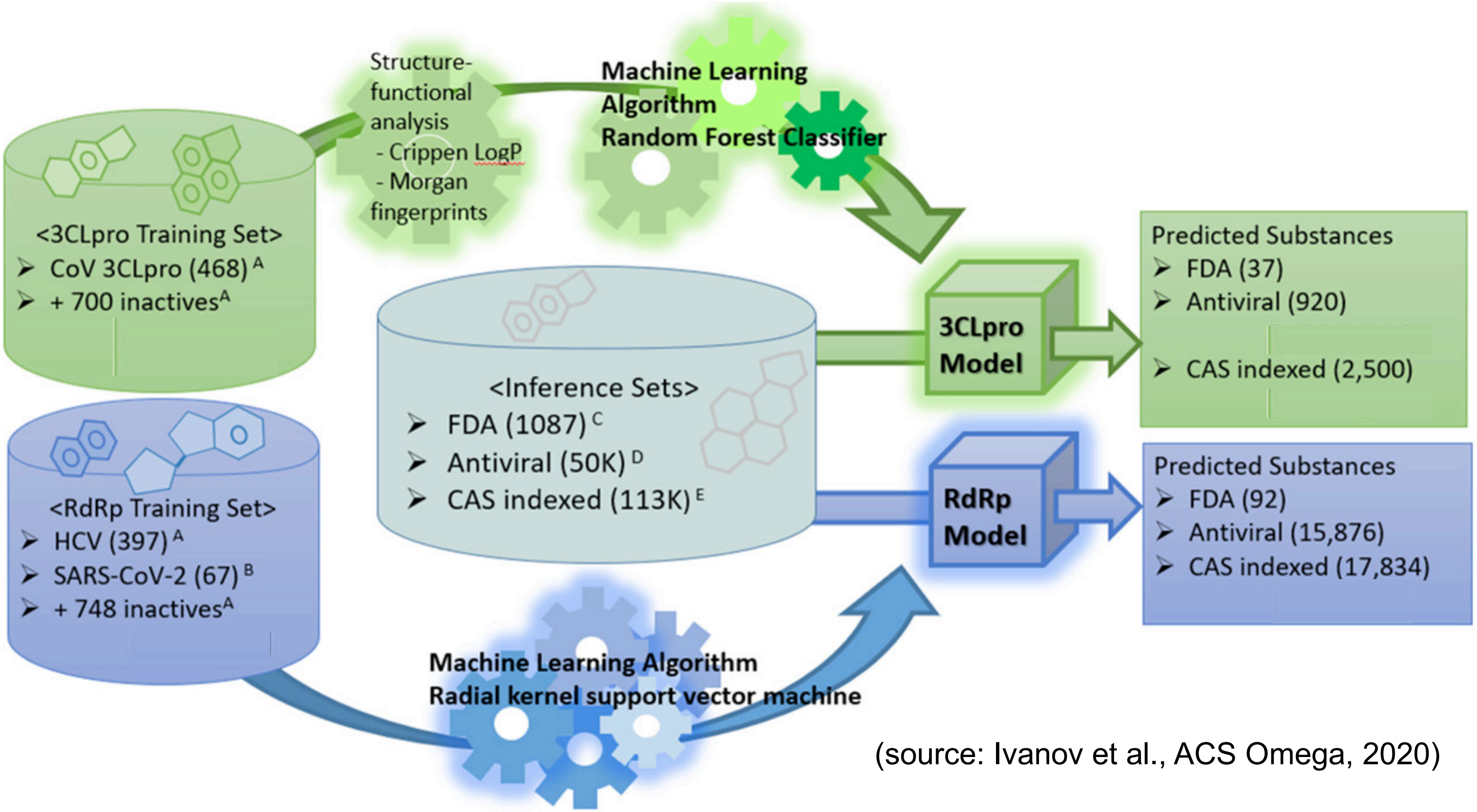
Inactive / low activity compounds





Application to SARS-CoV-2 compound screening

AI-based screening: Finding new inhibitors of viral proteins *3CLpro* and *RdRp*



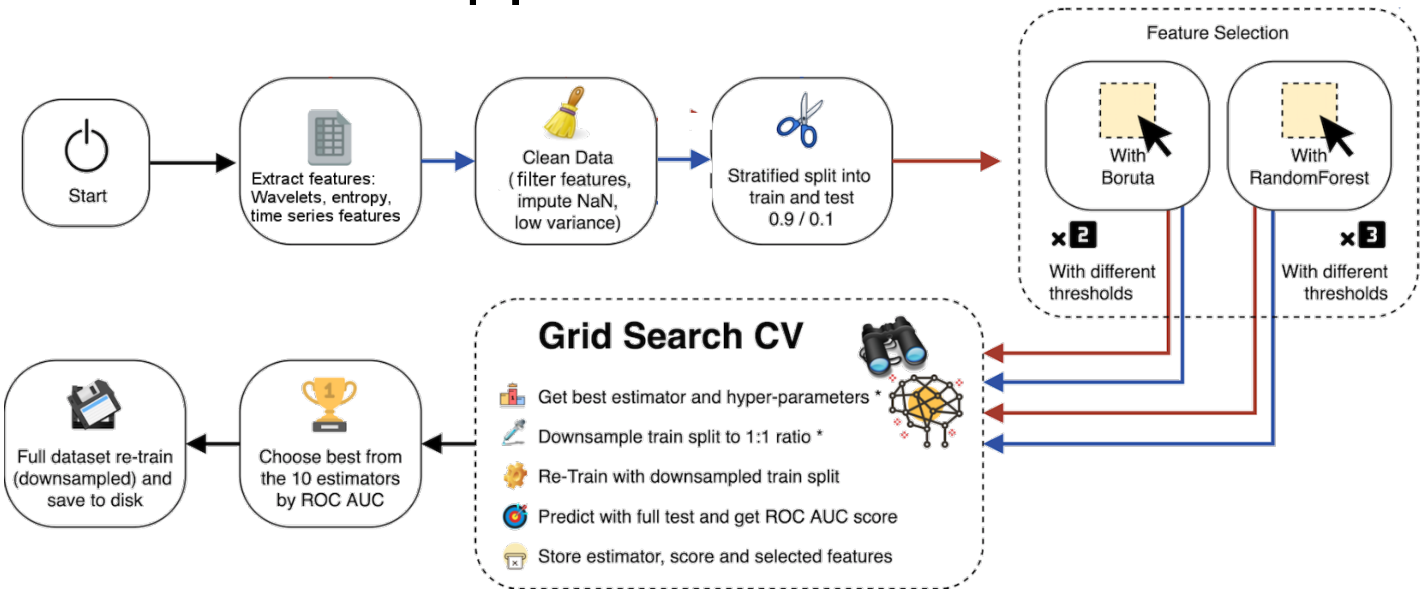
(source: Ivanov et al., ACS Omega, 2020)

AI for personalized health monitoring / digital biomarkers

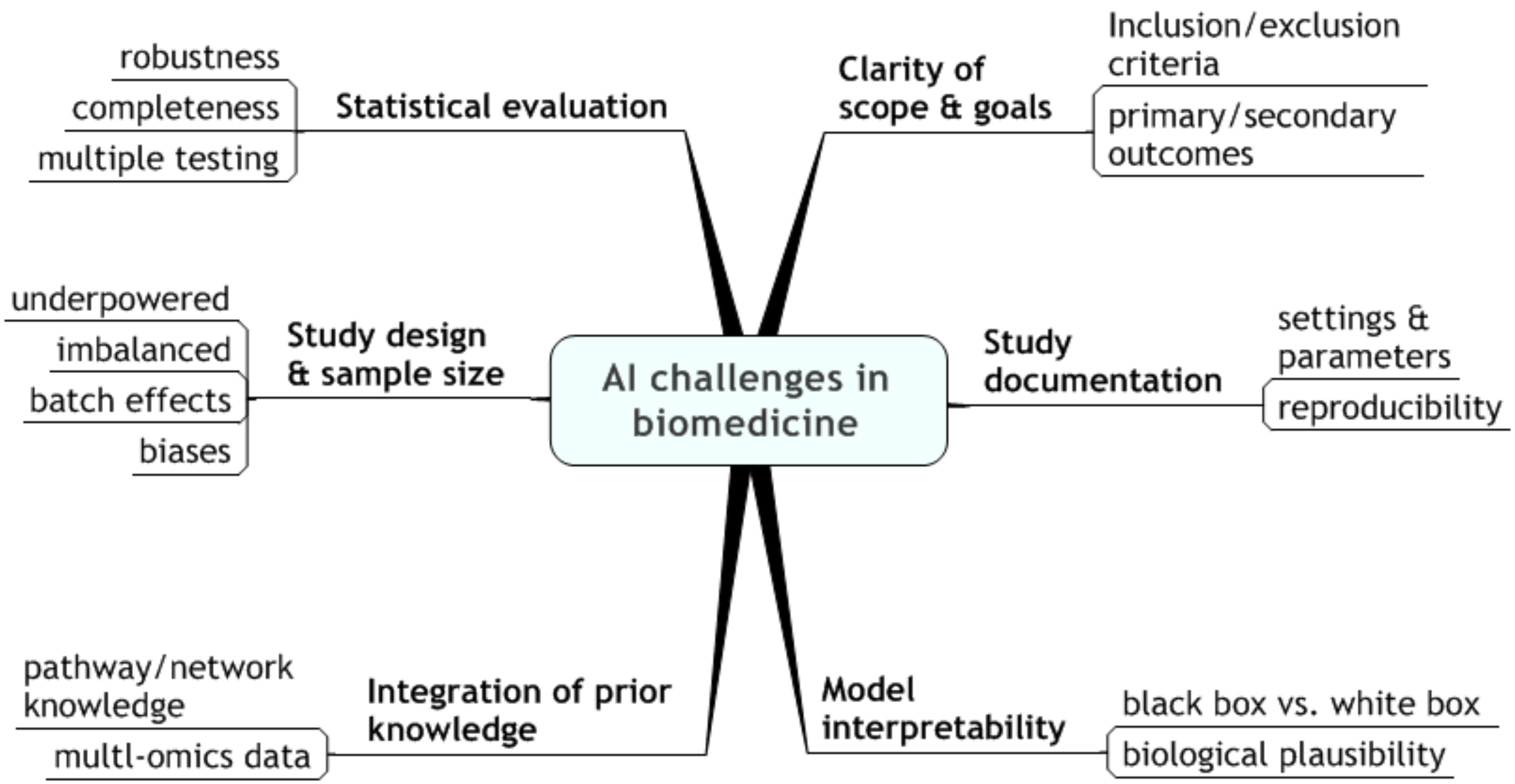
Digital biomarkers:

- mobile phone gyrometer & accelerometer
- gait sensors (eGaIT system)

Feature extraction & ML pipeline:



Common challenges for AI in personalized medicine



Recommendations from literature

Data pre-processing, filtering & normalization:

→ use cross-validation to check if pre-processing leads to information loss

→ compare or combine multiple pre-processing approaches

Integration of prior knowledge & multi-omics analyses:

→ Assess cost/benefit of multi-omics analyses using prior data, or conduct pilot analyses

→ use existing software & frameworks for integrative biological data analysis

Ensuring model interpretability & biological plausibility:

→ use dedicated methods to build interpretable models (e.g. rule learning methods)

→ use cellular pathway/network analysis & literature mining to guide modeling

Outlook: New AI strategies to address the challenges

Increase statistical power

→ AI-based integration of prior knowledge & multi-omics data

→ Algorithmic sample matching & selection, AI for batch adjustment

Increase model robustness

→ AI-based integration of models across human & animal model data, different experimental platforms and cohorts (Transfer learning)

Increase model interpretability

→ Structured and graph-based machine learning

→ AI-based literature mining for model interpretation

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Thank you for your attention!

Questions?

Comments?

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