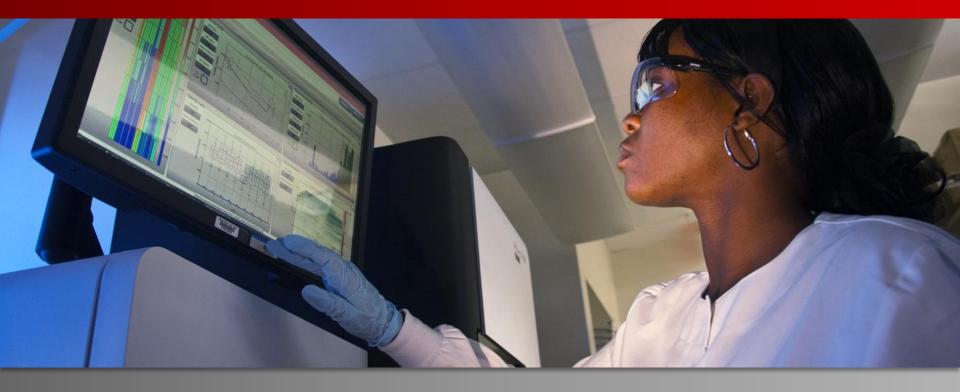
### Frederick National Laboratory for Cancer Research



### **Frontiers for Deep Learning and Cancer**

CANcer Distributed Learning Environment (CANDLE) Workshop February 21-22, 2018

> DEPARTMENT OF HEALTH AND HUMAN SERVICES • National Institutes of Health • National Cancer Institute Frederick National Laboratory is a federally funded research and development center operated by Leidos Biomedical Research, Inc., for the National Cancer Institute.

### Introduction

- Motivations
  - For workshop
  - For large scale computing in cancer research
- Joint Design for Advanced Computing Solutions for Cancer
- CANDLE and Deep Learning

### **Workshop Objectives**



- Overview of NCI and DOE collaborative efforts
- Grow community around deep learning applied to cancer and CANDLE (CANcer Distributed Learning Environment)
- Identify priority areas to explore challenges and opportunities

## **NIH CANDLE Workshop 2017**



- Participation included ~60 attendees spanning 13 NIH institutes, listed by breadth of attendance as follows:
  - NCI (30)
  - NHLBI (5)
  - NLM (4)
  - DRD (3)
  - CIT (2)
  - Netrias, LLC (1)
  - NHGRI (1)
  - NIA (1)
  - NIDCD (1)
  - NIDCR (1)
  - NIDDK (1)
  - NINDS (1)
  - IRSB (1)



- Take Away Points
- Request to establish trans-NIH Deep Learning group
- New use cases identified Applying deep learning to genomic data, imaging, data visualization, natural language processing
- Future CANDLE workshops are under development for anyone interested in deep/machine learning, or leveraging these to increase scientific productivity and accelerate cancer research

### NIH 2018 CANDLE Workshop February 21-22, 2018



### 2018 CANDLE Workshop registrants

### (> 100 participants):

- NCI (77)
- NIAID (14)
- CC (13)
- NLM (12)
- NHLBI (10)
- NIMH (10)
- NIDDK (8)
- CIT (6)
- OD (6)
- NIA (5)
- NICHD (5)
- NHGRI (4)
- NINDS (3)

- NCATS (3)
- NEI (2)
- NIAAA (2)
- NIAMS (2)
- NIBIB (2)
- NIDA (2)
- NIEHS (2)
- NIGMS (2)
- NIDCR (1)
- CSR (1)
- FIC (1)

- Machine Learning/Deep Learning topics of interest (top 5 survey responses) :
- Imaging
- Next-generation Sequencing
- Genomics and Genetics
- Text Analysis
- Big Data

## APPROXIMATE Level of adoption (beginner, intermediate, advanced):

- 100 introductory users
- 48 beginner-level adoption
- 30 intermediate
- 15 advanced users (not including instructors)

## Pushing the Frontiers of Cancer Research with Large Scale HPC



Challenge Problem	Need for Exascale
Mapping genetic susceptibility to cancer and its outcomes: investigate the contributions of genetic heritability to cancer and its outcomes, investigators must assess complex models of multiple gene-gene and gene-environmental interactions	Requires exascale computing to explore the interactions and develop subsequent robust models, including confirmation with large-scale permutation of parameters
Integrated genomic data analysis: numerous different types of genetic, genomic, and clinical data provides the insight to develop molecularly-targeted interventions	Requires exascale computing as combinatorial possibilities increase geometrically with the number of different genomic features considered
High-accuracy modeling of intracellular molecular signaling in complex mutational backgrounds: inform the critical pathways used, explore functionally- redundant signaling for inhibited pathways and bring greater awareness of complex interactions	Requires exascale computing to advance explorations of the large dynamic combinatorial multi-protein assemblies (membrane-associated and vary across cells, tissues and cancer types)

## Pushing the Frontiers of Cancer Research with Large Scale HPC



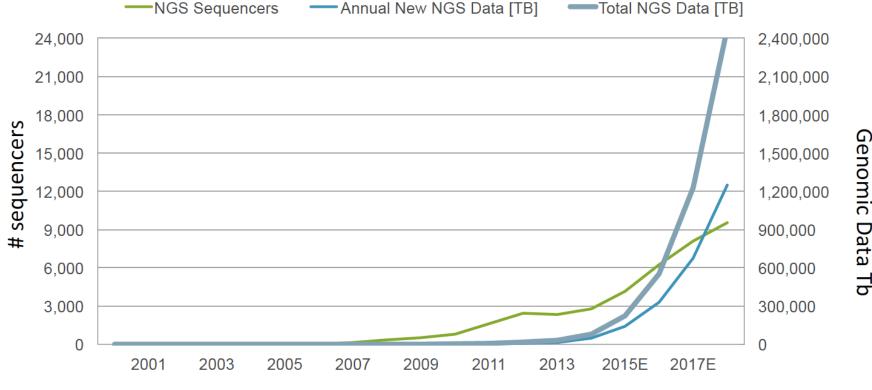
Challenge Problem	Need for Exascale
High-accuracy modeling of cancer drug interactions and reaction dynamics in complex mutational backgrounds: allow the study and modeling of critical aspects of a drug's mechanism of action across the full spectrum of possible mutational backgrounds	Requires exascale computing to evaluate reaction energies for extremely large systems in complex biological systems orders of magnitude greater than current capabilities
<i>In silico</i> characterization of 100 billion readily synthesizable potential cancer drugs: provide knowledge base of cost- effective, producible molecules characterized for potential clinical use and for future studies focusing on the system biology and dynamics of cancer	Requires exascale computing to support the generation and <i>in</i> <i>silico</i> characterization of more than 100 billion candidate molecules important to clinical and research applications in cancer
<b>Computing three-dimensional structures</b> <b>of RNA:</b> critical first step to understanding their function and activity and ultimately to the development of therapeutic agents targeting RNA molecules	Requires exascale computing to enable data collected from instrument observations to be used as a basis for accurate determination of previously unknown 3D topological structures of RNA

## **Pushing the Frontiers of Cancer Research with Large Scale HPC**



Challenge Problem	Need for Exascale
Accelerated characterization of biomolecular structures using advanced imaging techniques: ability to generate a more detailed biophysical profile for each patient will greatly improve diagnostic capabilities and expedite the delivery of precision medicine	Requires exascale computing to facilitate more rapid evaluation of higher-resolution images using significantly greater levels of optimal pattern registration and multi-modality data integration
Rapid characterization of bio-molecular dynamics and drug interactions from NMR data: provide essential knowledge of critical ligand interactions, biological complexes and interaction partners in cancer systems	Requires exascale computing to move this challenging manual problem into a computational domain to reduce the time required to interpret data from months to minutes
Integration of multi-modal experimental data to model macromolecular complexes: blend detailed physical studies with molecular and cellular biology to provide critical molecular insight in the development of new treatment modalities	Requires exascale computing to explore all possible inter-relationships and enable validation of the correlations through back-simulation of experimental data

# Amount of genomic data will exceed available resources



Between 2014-2018 production of new NGS data to exceed 2 Exabytes

NGS: Next Generation Sequencing

NGS sequencers include machines from Illumina, Life Technologies, and Pacific Biosciences. Human genome data based on estimates of whole human genomes sequenced Sources: Financial reports of Illumina, Life Technologies, Pacific Biosciences; revenue guidances; JP Morgan; The Economist; Seven Bridges Analysis.

### **Context for Advanced Computing**

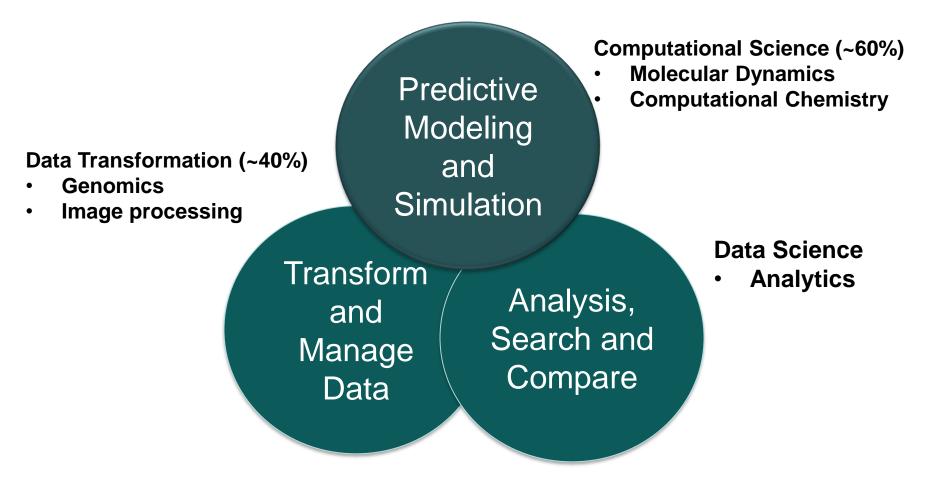


- Tools and cultures of HPC and Big Data have diverged to the detriment of both; unification essential to address major challenges
- The challenges of scale tax ability to transmit data, compute complicated functions, or store substantive portions; new approaches are needed
- International nature of science demands further development of advanced computer architectures and global standards for processing data, even as international competitiveness complicates the openness of the scientific process

Source – Reed and Dongarra – Communications of the ACM, July 2015 (vol 57, no 7)

### **Expanding Role of HPC in Cancer**





(Estimated usage numbers for provided by Sean Davis, NCI Center for Cancer Research)

### **Advancing Precision Oncology**



#### NATIONAL CANCER INSTITUTE ADVANCING PRECISION ONCOLOGY UNDER THE NATIONAL PRECISION MEDICINE INITIATIV Precision oncology: using molecular information about a patient's cancer to inform To make precision oncology a reality in everyday clinical practice, NCI is leading research to: EXPAND PRECISION MEDICINE CLINICAL OVERCOME DRUG RESISTANCE STUDIES TO ADULTS AND CHILDREN IN THEIR COMMUNITIES to learn why cancer treatments stor to test new cancer treatments working in many patients INCREASE THE NUMBER OF LABORATORY KNOWLEDGE NETWORK THAT MODELS OF HUMAN CANCER WITH CLINICAL INFORMATION to test potential treatments and learn more about to serve as a resource for scientists, health cell changes that drive cancer care professionals, and patients



### INTEGRATES CANCER GENOMIC INFORMATION

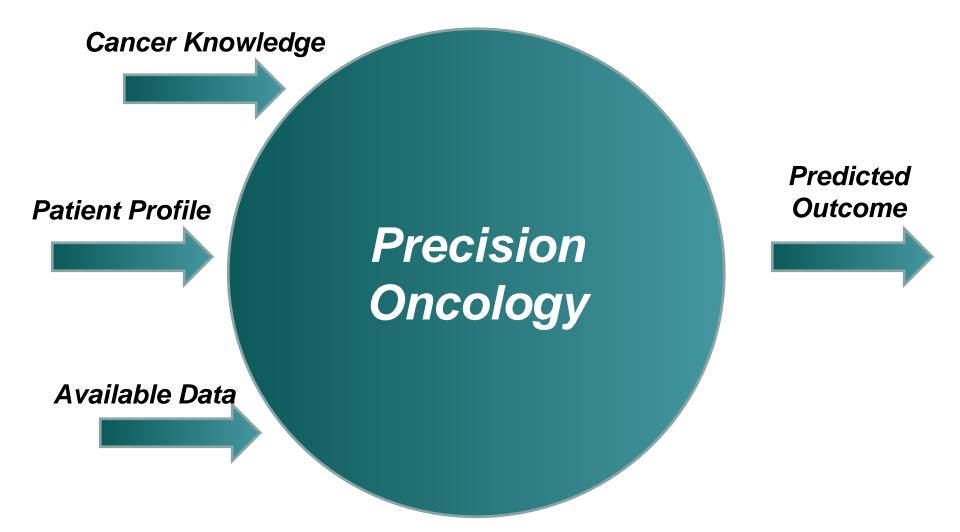


www.cancer.gov/precision-medicine

**NCI** Mission (under National Precision **Medicine** Initiative)

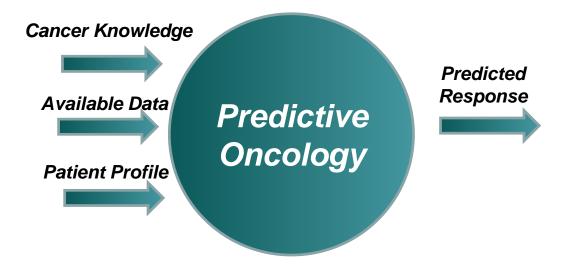
- Accelerating ulletdevelopment of new treatment options
- Overcome drug ۲ resistance
- Increase number of • laboratory models
- Build an integrated  $\bullet$ knowledge network

### **HPC Enabling Precision Medicine**



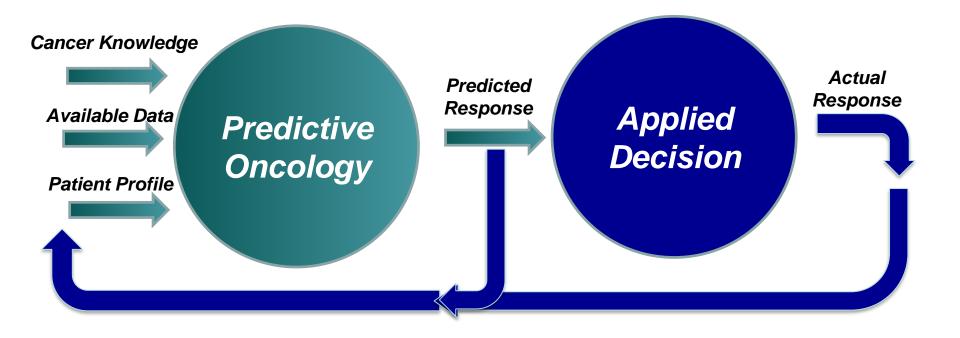
### **Predictive Oncology**





### **Oncology Learning System**





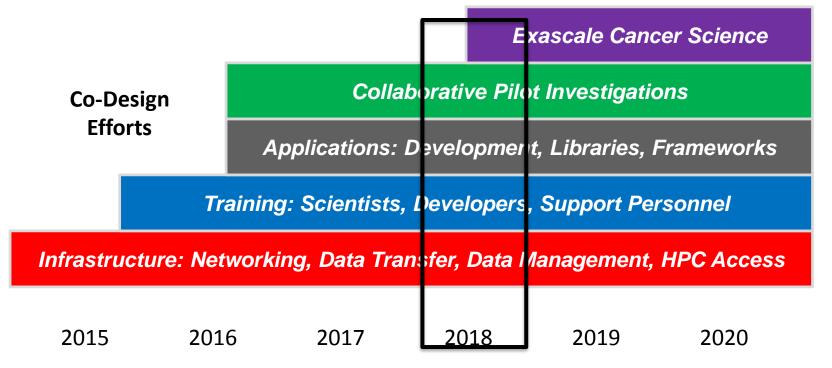
### **Exascale Cancer Science**



Exascale in a nutshell:

- Millions of CPU cores contributing to a single task
- Nearly 1000 times faster than fastest computer today
- Focus of DOE Advanced Strategic Computing





### **NCI-DOE Collaboration Pilots:** Advancing Precision Oncology



### NATIONAL CANCER INSTITUTE ADVANCING PRECISION ONCOLOGY

UNDER THE NATIONAL PRECISION MEDICINE INITIATIV

Precision oncology: using molecular information about a patient's cancer to inform treatment

To make precision oncology a reality in everyday clinical practice, NCI is leading research to:

NCI Mission Impact: Accelerating development of new treatment options for precision cohorts

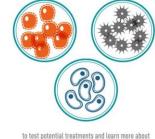
Pilot 1: Pre-clinical Models Predictive patient drug response models with advanced computing





to test new cancer treatments

INCREASE THE NUMBER OF LABORATORY MODELS OF HUMAN CANCER



cell changes that drive cancer





to learn why cancer treatments stop working in many patients

BUILD A KNOWLEDGE NETWORK THAT INTEGRATES CANCER GENOMIC INFORMATION WITH CLINICAL INFORMATION



to serve as a resource for scientists, health care professionals, and patients

www.cancer.gov/precision-medicine

Pilot 2: Biological Models *Multi-scale* computational biological models

Pilot 3: Cancer Surveillance Computational insight into factors impacting clinical response

### **Integrated Precision Oncology**



Pilot 1 Pre-clinical Model Development



Aim 1: Predictive Models of Drug Response (signatures)

Aim 2: Uncertainty Quantification and Improved Experimental Design

Aim 3: Develop Hybrid Predictive Models Pilot 2 RAS Therapeutic Targets



Aim 1: Adaptive time and length scaling in dynamic multi-scale simulations

Aim 2: Validated model for Extended RAS/RAScomplex interactions

Aim 3: Development of machine learning for dynamic model validation

Pilot 3 Precision Oncology Surveillance



Aim 1: Information Capture Using NLP and Deep Learning Algorithms

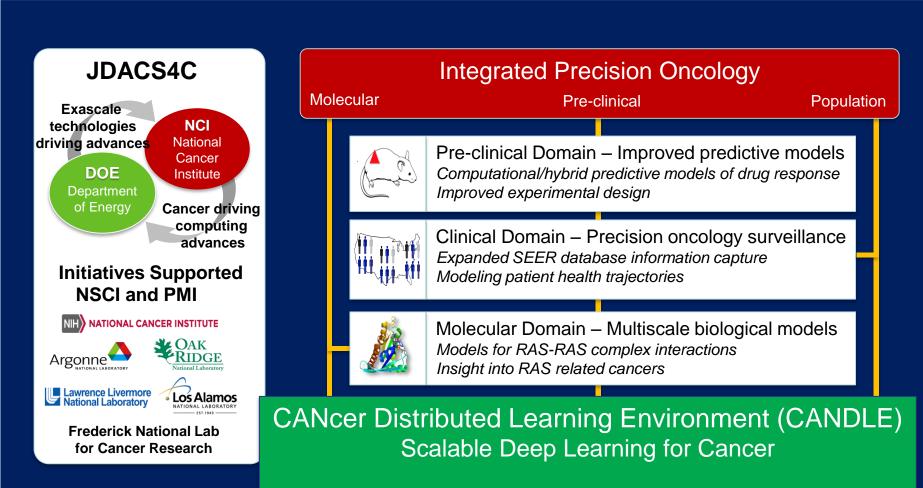
Aim 2: Information Integration and Analysis for extreme scale heterogeneous data

Aim 3: Modeling for patient health trajectories

Crosscut: CANDLE exascale technologies, uncertainty quantification

## Joint Design of Advanced Computing Solutions for Cancer





JDACS4C established June 27, 2016 with signed MOU between NCI and DOE

### **Integrated Precision Oncology**



### **Crosscut: Integrated Precision and Predictive Oncology**

Pilot 1 Pre-clinical Model Development



Aim 1: Predictive Models of Drug Response (signatures)

Aim 2: Uncertainty Quantification and Improved Experimental Design

Aim 3: Develop Hybrid Predictive Models Pilot 2 RAS Therapeutic Targets



Aim 1: Adaptive time and length scaling in dynamic multi-scale simulations

Aim 2: Validated model for Extended RAS/RAScomplex interactions

Aim 3: Development of machine learning for dynamic model validation

Pilot 3 Precision Oncology Surveillance



Aim 1: Information Capture Using NLP and Deep Learning Algorithms

Aim 2: Information Integration and Analysis for extreme scale heterogeneous data

Aim 3: Modeling for patient health trajectories

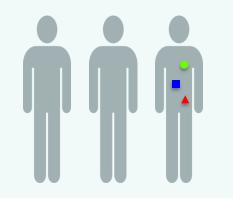
Crosscut: CANDLE exascale technologies, uncertainty quantification

## **Molecular Scale Pilot**



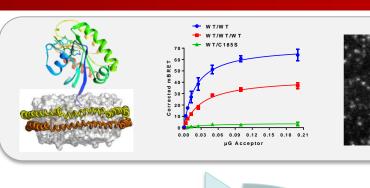
30% of cancers have mutated RAS

~1M deaths/year



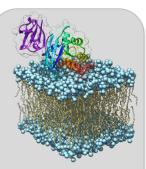
Current therapies ineffective against RAS-driven cancer

Facilitate discovery and development of novel therapeutics



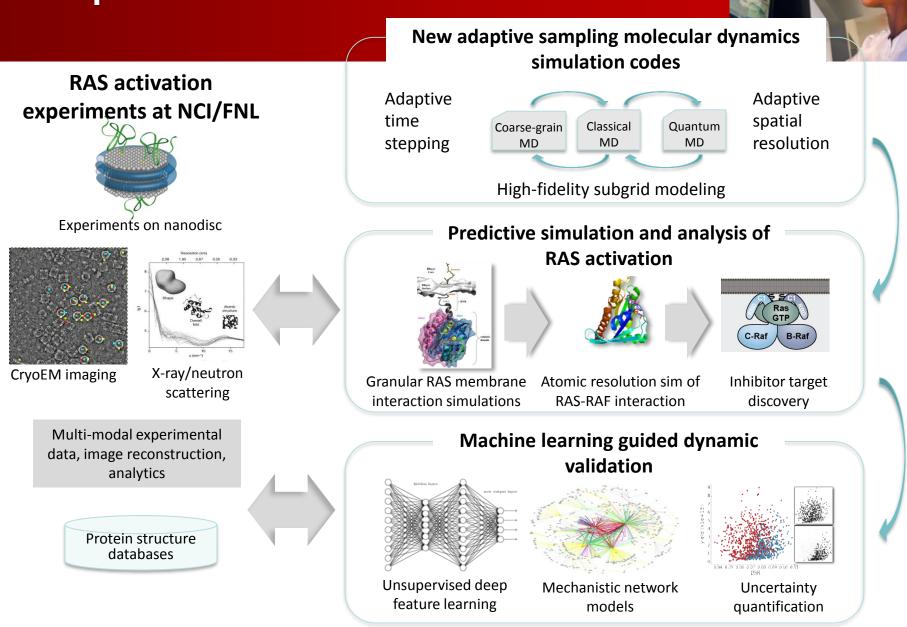
Molecular Dynamics Simulation Modeling





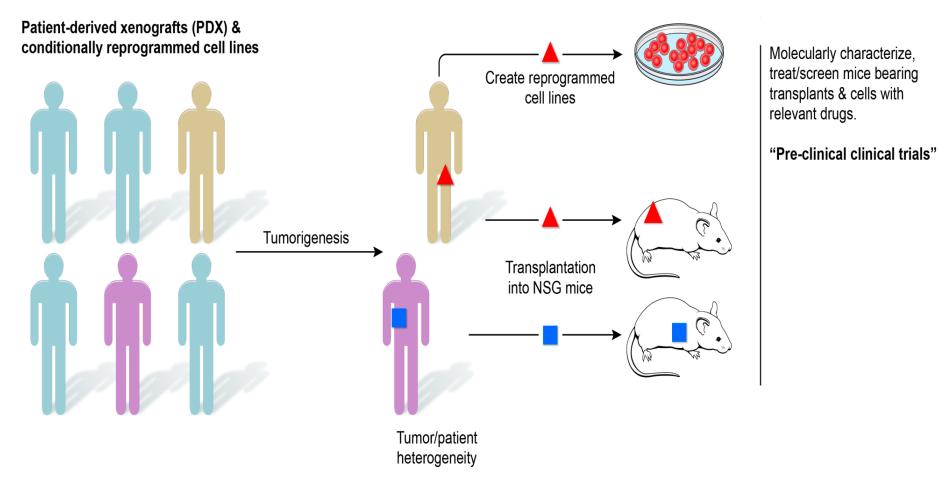
RAS biology ID targets New inhibitors Pilot 2 – Exascale Co-Design

### **RAS proteins in membranes**



## **Pre-clinical Focused Pilot**

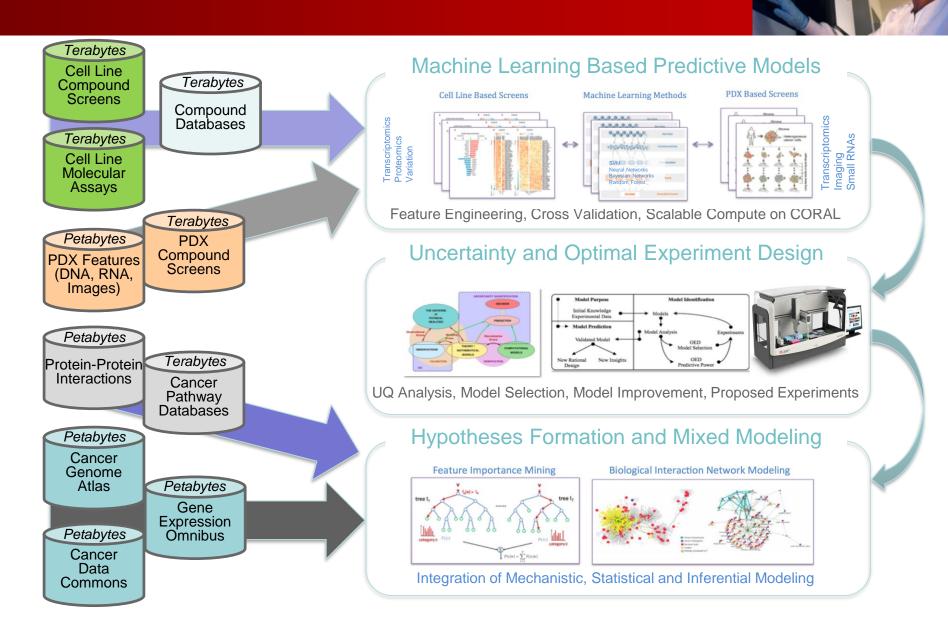




Nature Rev. Clin. Oncol. 11: 649-662, 2014.

### **Pilot 1 – Exascale Technologies**

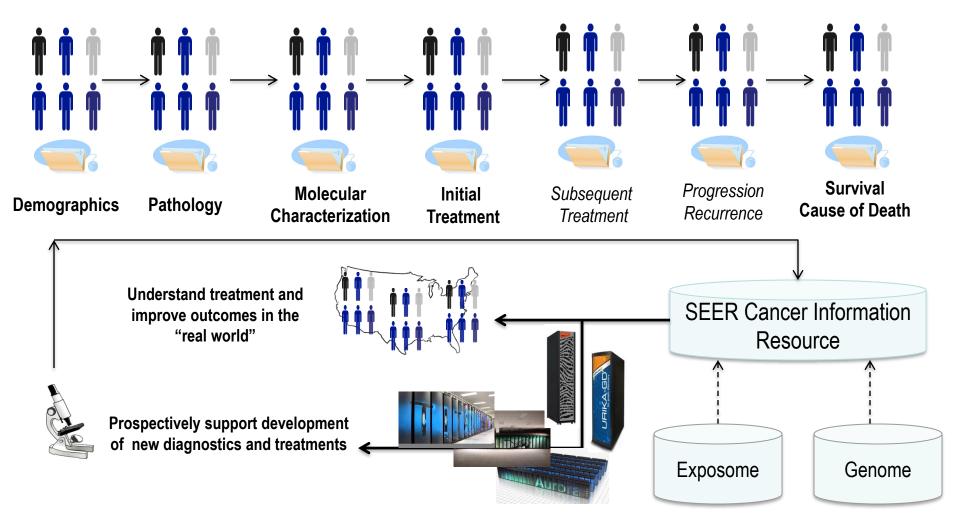
## Predictive models for pre-clinical screening



## Population Focused Pilot

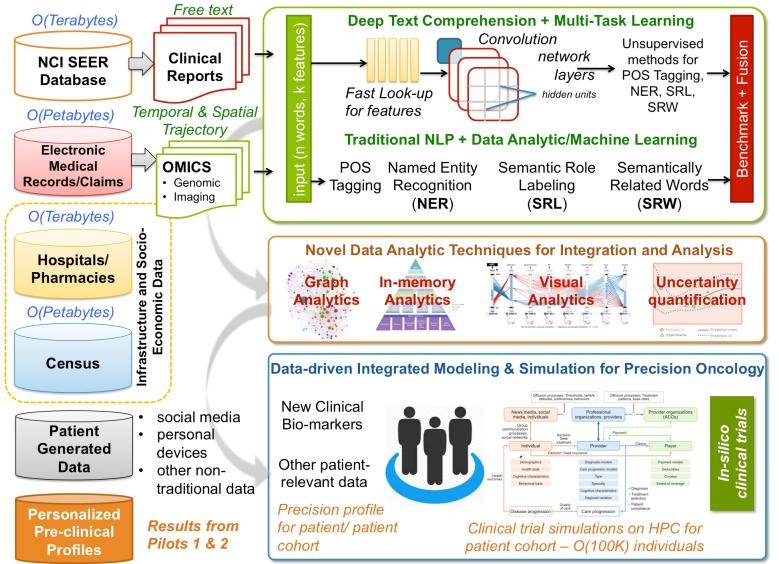


Surveillance data captured on each cancer patient for the entire population



### Pilot 3 – Exascale/Big Data Intersection Population information integration, analysis and modeling

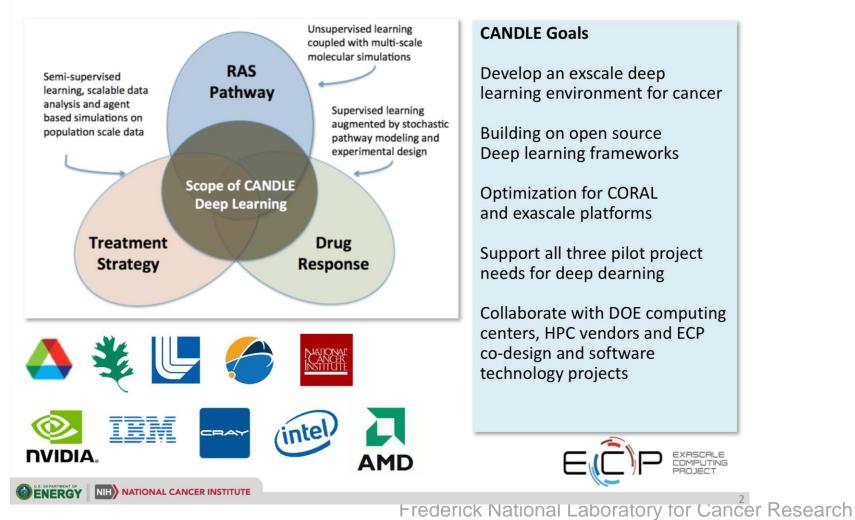




### CANDLE – Deep Learning Across JDACS4C



### **ECP-CANDLE Project : CANcer Deep Learning Environment**



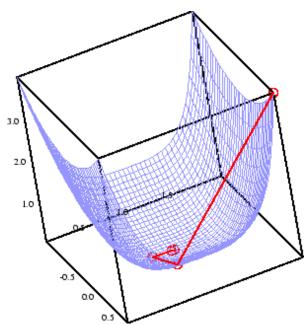
### CANDLE – CANcer Distributed Learning Environment



- CANDLE is DOE Funded contribution to JDACS4C
- Four year project (now in year 2)
- Focuses on creating scalable, open and portable Deep Learning framework
- Supports Deep Learning needs for all JDACS4C pilots
  - DOE scientific leads bring pilot-specific deep learning challenges
- Open source software release
- FNL brings NCI connection to CANDLE
  - Translating computational environment to broader cancer research community
  - Portability and standardization of model representations
  - Conventions and methods for model validation and evaluation in cancer

### Optimization

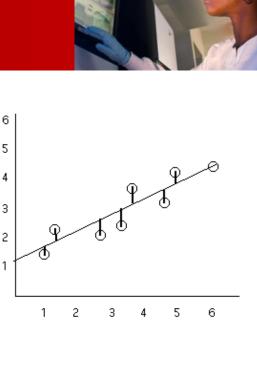
- Decision variables
  - Elements that can be adjusted to change the output of the objective functions
  - For example:  $x_1, x_2, x_3, x_4, \dots, x_n$
- Objective functions
  - Functions that determine improved combination of decision variables
  - Objective =  $F(x_1, x_2, x_3, x_4, \dots, x_n)$
- Constraints
  - Limits on possible values of decision variables

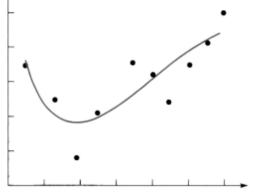




### **Least Squares Optimization**

- Decision variables
  - Elements that can be adjusted to change the output of the objective functions
  - Choice of function
    - Linear: **y** = a**x** + b
    - Quadratic:  $\mathbf{y} = a\mathbf{x}^2 + b\mathbf{x} + c$
- Objective functions
  - Functions that determine improved combination of decision variables
  - Minimizing distance between  $y_{pred}(x_i)$  and  $y_{actual}$  across all points

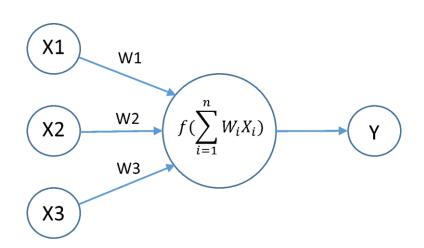






### **Machine Learning Models**

- Prototype: Artificial Neural Networks
- Each node employs inputs, weights, and activation function to deliver outputs
- Employ multiple nodes and functions
- Creating a network among nodes



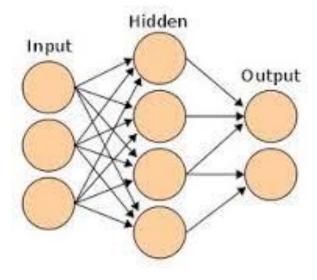
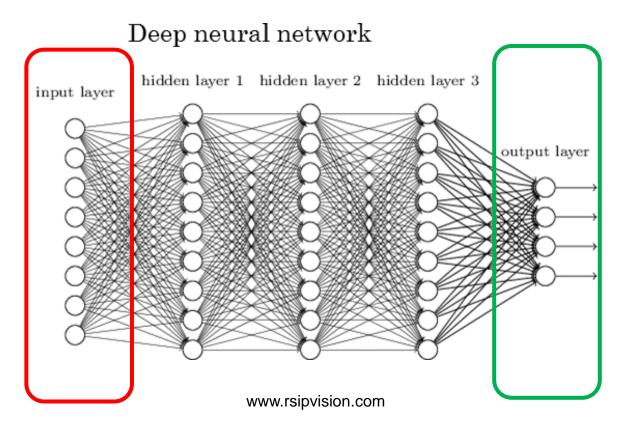


Image from mathworks.com



### **Deep Learning Models**

- Large number of nodes
- Multiple layer configuration
- Enables combinations of non-linear functions
- Provides flexibility to detect subtle features



### **Deep Learning and Optimization**

- Decision variables include
  - Connections within the network (topology)
  - Mathematical functions used in the network
  - Weights and parameters
- Objective function
  - Minimize differences between actual outcomes and predicted outcomes
  - Y<sub>pred</sub> = DL(input values)
  - $\Sigma(y_{pred} y_{actual})^2$
- Constraints
  - Specific ranges and relationships enforced among decision variables



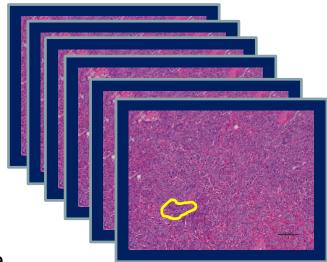




## **Deep Learning**

- Applications
  - Classification
  - Clustering
  - Prediction
- Basic data requirements
  - Relevant data
  - Consistent formatting vector of input data
  - Well annotated/labeled for outcome
  - Accessible quantity
- Basic development process
  - Train optimize decision variables to minimize differences between DL outcomes and actual outcomes across large datasets
  - Validate evaluate relative to chosen data Frederick National Laboratory for Cancer Research





## Deep learning identifying skin cancer

- Paper in February 2, 2017 issue of Nature
- Matched performance of dermatologists
- Data
  - 130,000 visual images of skin cancer
  - Processed to harmonize data available from multiple sources
  - Developed annotation to differentiate types of cancer
  - Fed as raw pixels
- Leveraged algorithm used by Google to efficiently train
- Validated
  - using only high-quality, biopsy confirmed images
  - Compared results to human expert analysis
- Potential for algorithm to be deployed on smart phones

## Recent applications of deep learning applied to cancer



Deep Learning in Drug Discovery Wiley online, December 30, 2015

Deep learning algorithm does as well as dermatologists in identifying skin cancer -Stanford News, January 25, 2017

Detecting Cancer Metastases on Gigapixel Pathology Images -Cornell University Library, March 3, 2017

Deep Learning Drops Error Rate for Breast Cancer Diagnoses by 85% -2016 Camelyon Grand Challenge

Accelerating cancer research with deep learning -Phys.org, November 9, 2016

H&E-stained Whole Slide Image Deep Learning Predicts SPOP Mutation States in Prostate Cancer bioRxiv, March 27, 2017

Deep learning application trial to lung cancer diagnosis for medical sensor systems -IEEE 2016 International SoC Design Conference (ISOCC)

Deep learning and 3D-DESI imaging reveal the hidden metabolic heterogeneity of cancer -Chemical Science, 2017

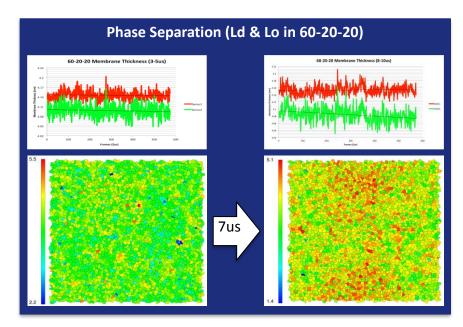
### **Challenge 2: RAS/RAF Pathway Prediction**

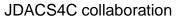


Develop and test mechanistic models informed by cancer biology, structure and functional data that predict biophysical properties of normal and mutant proteins

Requires large-scale networks to train, and the generated models run on large-scale input data to produce actionable results:

- After completion of simulation scenarios, the DNN would be re-trained to select/determine the next set of exascale MD simulations to be run (considering ~10<sup>9</sup> alternatives)
- Neighborhoods in MD data sets will be defined to include ~10<sup>3</sup> particles and cover ~10<sup>3</sup> time steps producing an input vector dimension of ~10<sup>6</sup>
- Large-scale MD simulations will provide a few billions of these neighborhood-based vectors as a training set for feature learning
- An MD data set with 10<sup>6</sup> particles and 10<sup>9</sup> time steps will provide ~10<sup>9</sup> neighborhood training vectors





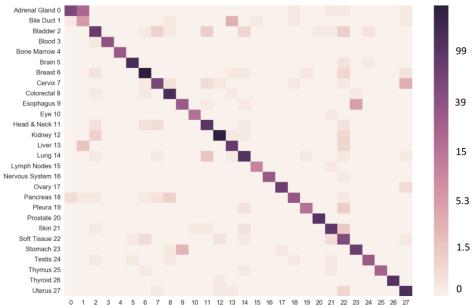
### **Challenge 1: Drug Response Prediction**



# Develop and test predictive models for patient outcomes based on clinical and pre-clinical genomic and molecular signatures

## Requires exascale class simulation runs and data analysis coupled with the deep learning:

- After training the network on millions of previous screen results, the DNN would be used to search through up to 10<sup>9</sup> combinations of drugs to find those predicted to maximally inhibit a given tumor, or to search through 10<sup>9</sup> hypothetical compounds to identify those with potential as new drug development candidates
- For a given drug-tumor pair in a treatment, at least 10<sup>7</sup> features describe the input data; these features include 10<sup>6</sup> properties of the drug and 10<sup>7</sup> measurements of tumor molecular characteristics
- Access to ~10<sup>7</sup> samples of drug screening results, input data for supervised deep learning is a 10<sup>7</sup> x 10<sup>7</sup> mostly dense matrix (~1PB) with redundancy



#### JDACS4C collaboration

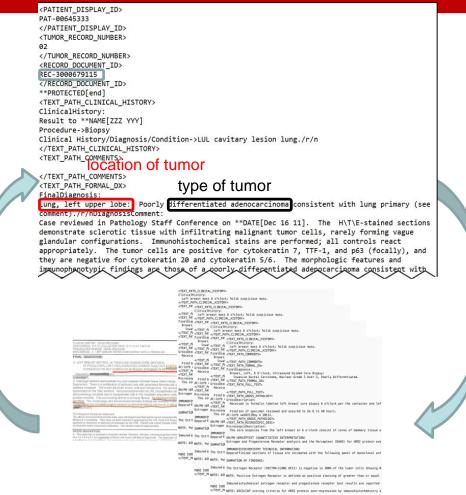
### **Challenge 3: Treatment Strategy Prediction**



## Expand utilization of population-based cancer data for understanding therapy, care choices, and patient outcomes

#### Requires exascale for the training problems and use the resulting models to advance cancer problem area:

- Use labeled pathology reports to train the NLP system to read and understand the millions of unlabeled datasets and translate them into structured data that can be used for advanced analytics to drive large-scale agent based models of treatment strategies
- Conservative estimation of a million (10<sup>6</sup>) pathology reports; a typical pathology report consists of approximately 15,000-20,000 words, with ~O(10<sup>6</sup>) words
- For text comprehension, the number of outputs can vary between 10<sup>3</sup>-10<sup>4</sup>
- Expect to bring in additional data that include many different modalities, including pan-omic datasets



#### Acknowledgements

- NCI CBIIT
  - Warren Kibbe, Tony Kerlavage, Carl McCabe
  - NCIP Cloud Pilot Team
  - Cancer Informatics Branch
  - Many more
- NCI Division of Cancer Control and Population Studies
  - Lynne Penberthy, Paul Fearn
- NCI Division of Cancer Therapeutics and Diagnostics
  - Jim Doroshow
- FNLCR
  - Data Science and Information Technology Program
  - Jack Collins (ABCC), Greg Warth (ITOG), Braulio Cabral (CBIIT Support), Megan Kaminiski (PMO)
  - Dwight Nissley, Yvonne Evrard, Frank McCormick(UCSF)



- Department of Energy
  - Dimitri Kusnezov
- Lawrence Livermore National Laboratory
  - Amy Gryshuk, Jim Brase, Jason Paragas, David Rakestraw, Fred Streitz, Felice Lightstone, Ken Turtletaub, Brian van Essen
- Argonne National Laboratory
  - Rick Stevens
- Los Alamos National Laboratory
  - Frank Alexander
- Oak Ridge National Laboratory
  - Gina Tourassi
  - Gil Weigand
- And many, many more

#### **Workshop Aims**



- Overview of NCI and DOE collaborative efforts
- Grow community around deep learning applied to cancer and CANDLE (CANcer Distributed Learning Environment)
- Identify priority areas to explore challenges and opportunities
  - Deep learning in cancer research today
  - Sources of cancer data today and the future
  - Validating, sharing and extending deep learning models

## Questions

• Discussion.

- Contact info:
  - Eric.Stahlberg@nih.gov

#### **Presentation Overview**



#### Common Thread

Support efforts to establish high-performance computing foundations for accelerated predictive oncology and cancer precision medicine

#### Context

- Frederick National Laboratory
- Data Science and IT Program
- Precision Oncology
- Computational and Data Challenges

#### NCI-DOE JDACS4C Pilots

- Motivations
- Pilot 1 Molecular domain
- Pilot 2 Preclinical domain
- Pilot 3 Population domain
- Broader Engagement
  - CANDLE CANcer Distributed Learning Environment
  - Workshops

### Overview of Frederick National Laboratory for Cancer Research (FNLCR)

- FNLCR is the only Federally Funded Research and Development Center (FFRDC) dedicated exclusively to biomedical research
  - Operated in the public interest by Leidos Biomedical Research, Inc (formerly SAIC-Frederick) on behalf of the National Cancer Institute
- Main campus located on 70 acres at Ft. Detrick, MD
  - Leidos Biomed employees co-located with NCI researchers and other contractors on the NCI Campus at Frederick
  - Additional Leidos Biomed scientists at Bethesda and Rockville sites





#### Mission

Provide a unique national resource for the development of new technologies and the translation of basic science discoveries into novel agents for the prevention, diagnosis and treatment of cancer and AIDS.

#### nflammation

#### Frederick National Laboratory for Cancer Research

## **Research & Development at FNLCR**

#### Research & Development

- **Basic Research**: New knowledge about AIDS and cancer
- **Applied R&D**: New diagnostics and therapeutics
- **Clinical Research:** Clinical trials and laboratory analysis
- **cGMP manufacturing:** Biologicals and vaccine production

#### Specialties

- Genomics, proteomics, and metabolomics
- Bioinformatics and imaging
- Nanotechnology
- Animal models
- Tumor cell biology and virology
- Immunology and inflammation
- Data Science and Information Technology underpin and support all R&D activities and specialties









#### Data Science and Information Technology Program



**Mission:** Leverage leading edge data science and information technology skills, tools, and capabilities to accelerate translation of biomedical data to scientific discoveries, medical treatments, diagnostic and prevention tools for cancer and AIDS patients.

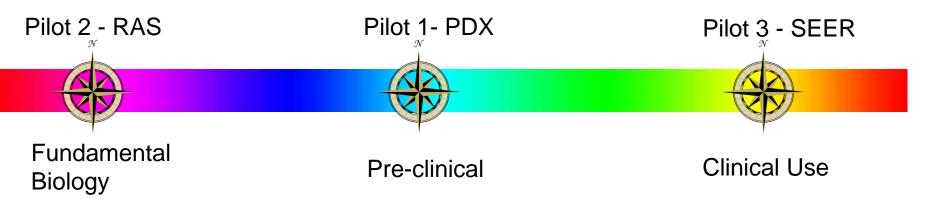


Enabling physicians, scientists, and patients to make critical decisions based on knowledge gained from <u>all</u> and not only a fraction of data and information available to them.



#### A New Era for Data and Computational Science Applied to Cancer





- Three pilots in 3 priority areas
- Efforts inform future data and computing science needs
- Efforts beyond pilots needed to extend and accelerate across the complex cancer research and clinical spectrum
  - New technologies to probe and observe cancer at all scales, conditions, types, contexts
  - Much more larger, different and newer data

### **Getting Connected**



- CANDLE Workshop at NIH
  - April 18-19, 2018
- GPU Technology Conference
  - May 9, 2017 CANDLE workshop
- Precision Medicine Workshop
  - June 22, 2017 First workshop scheduled for ISC17
- Computational Approaches for Cancer Workshop (CAFCW)
  - November 2017 Third workshop proposed for SC17

#### NCI Precision Oncology Extending the Frontiers



- Identify promising new treatment options through the use of advanced computation to rapidly develop, test and validate predictive pre-clinical models for precision oncology.
- Deepen understanding of cancer biology and identify new drugs through the integrated development and use of new simulations, predictive models and next-generation experimental data.
- Transform cancer care by applying advanced computational capabilities to population-based cancer data to understand the impact of new diagnostics, treatments and patient factors in real world patients.

#### **Predictive Models**



### **Precision Oncology and Computing**

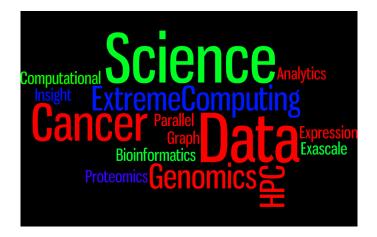
#### Motivations

- Derive value from growing volumes, types and sources of data and information
- Expanding support for growing data and computational science needs and opportunities
- Essential to future mission success

#### Challenges

- Limited resources
- Limited expertise in new areas
- Rapidly growing data requirements

Aims



Support efforts to establish high-performance computing foundations for predictive oncology and cancer precision medicine

### **Emerging Opportunities**

- Drug and treatment discovery
  - ATOM Accelerating Therapeutics for Opportunities in Medicine
- Increased use of imaging based observations in research
  - Molecular scale observations
  - Pre-clinical domain
- Increased use of imaging in clinical settings
  - Diagnostics
  - Non or minimally invasive post-treatment monitoring
- Integration of imaging modalities and fusion of information sources
- Predictive/analytic model verification, evaluation and validation