





DEEP LEARNING AND THE TRANSFORMATION OF SCIENTIFIC EXPLORATION



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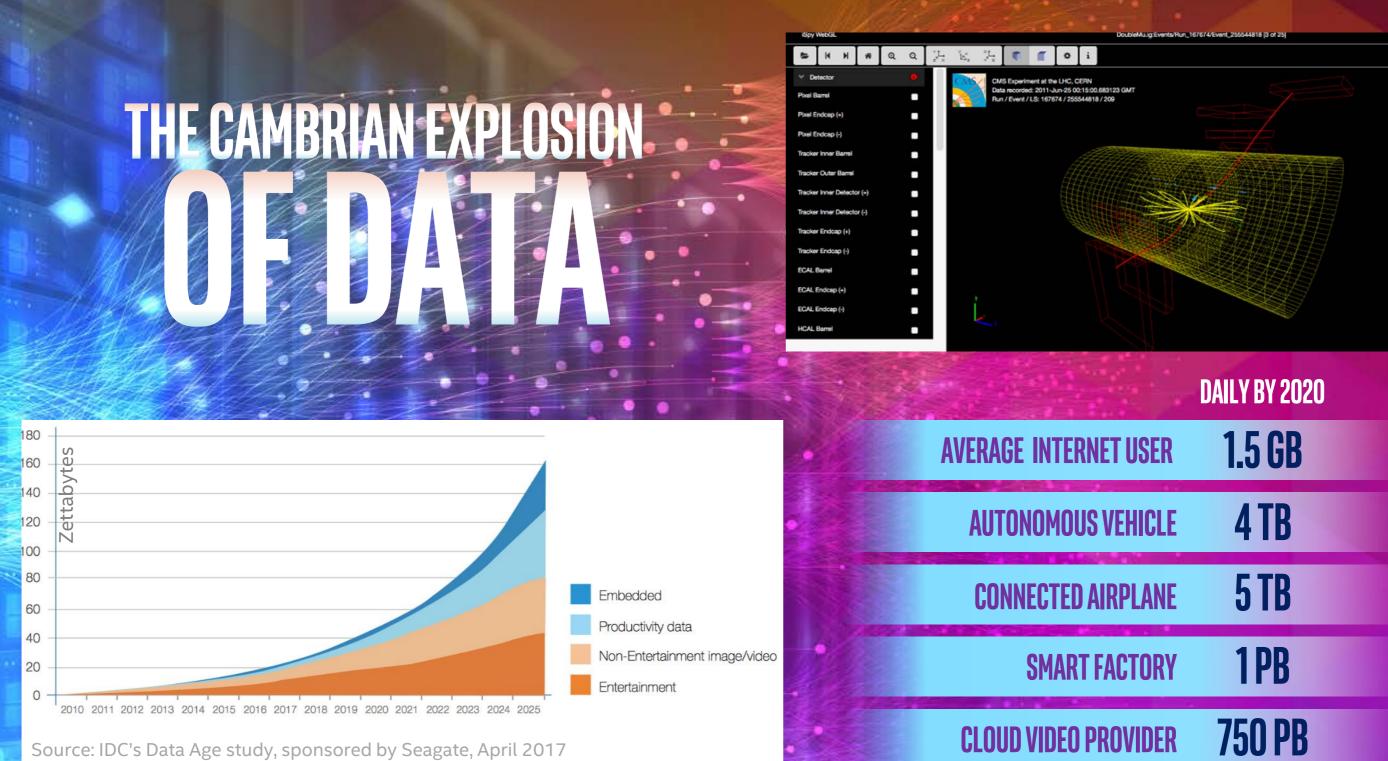
THE RISE OF AI-ENRICHED SCENTIFIC EXPLORATION

SCIENTIFIC PARADIGMS EMPIRICAL THEORETICAL COMPUTATIONAL



DATA EXPLORATION (PROGRAMMED) PHENOMENON EXPLORATION (ML)





ZETTA DATA × EXA COMPUTING × MACHINE LEARNING



EHICLE	4 TB
PLANE	5 TB
CTORY	1PB

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ER	1	5	GB

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MACHINE LEARNING DEEP LEARNING DEEP LEARNING IN HPC AND SCIENCE

ARTIFICIAL

INTELLIGENCE

REAR FACING CAMERA

ADAS

SPEECH

TYPES OF ANALYTICS/ML (PARTIAL LIST)

LATERAL CAMERA

CLASSIFICATION

REGRESSION

CLUSTERING

FEATURE LEARNING

ANOMALY DETECTION



FRONT FACING CAMERAS

ALPHA GO





MACHINE LEARNING CLASSES OF APPLICATION SCHEMES

SPACE EXPLORATION

FORM SPOTTING

> TRACKING ESTIMATION



TRIBUTARIES CURATION

> $p_T = 173.7 \text{ Ge}$ $\eta = -0.43$ $\phi = -2.14$

 $p_T = 61.1 \text{ GeV}$ $\eta = 0.14$ $\phi = 1.08$

 $p_T = 9.4 \text{ GeV}$ $\eta = -0.45$ $\phi = -2.17$



True

ects.a



FORM SPOTTING **FINDING A BLADE OF GRASS IN A HAYSTACK**

- Finding a 'kind of pattern' in multi-dimensional elaborate data
- Lots of examples available
- Weak signal in a sea of noise
- No mathematical/statistical model

Applicable DL techniques: Pattern classification Feature learning Anomaly detection **Supervised learning:**

Data tagging



FORM SPOTTING NEUROSCIENCE



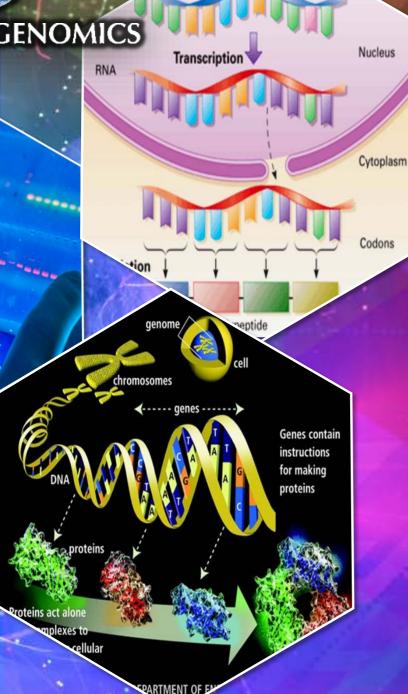
http://brainiak.org

Princeton Neuroscience Institute mapped the human mind in real time for improved diagnosis and treatment of brain disorders and mental illness. Typical single scan (~1 million voxels) evaluated in seconds vs hours. BrainIAK - Developing the next generation in fMRI brain imaging.





SYNTHETIC GENOMICS

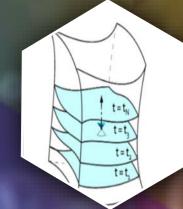


FORM SPOTTING GENOMICS

- 10⁴x speed up boost: annotate 1 million genes in <1hr vs. weeks with traditional tools
- Assign function to millions of uncharacterized proteins
 - Semantic Search: discover proteins with related function even without sequence similarity
 - Early stages of protein design: predict in seconds impact of every possible AA change

Joint effort of SGI and Intel





 $\varphi(t_1 - \Delta t)$

TRACKER

TRACKING ESTMATION

Well defined functions/model; compute intensive Major reduction (e.g., 10⁴ x) required to enable real-time or rapid iterations **Applicable DL techniques:** Regression Supervised learning: Full model training the DL Shadowing **Estimator**





- Laser Interferometer Gravitational-Wave **Observatory (LIGO) labs**
- Detection of gravitational waves from binary black hole mergers
- Process array of sensors for directing a highfocus radio telescope
- Real-time multimessenger detection (DNN) >10⁴ speedup: multiple days to 'real-time' (George, D., Huerta, E. A.: Deep Neural Networks to Enable Real-time Multimessenger Astrophysics)

https://www.ligo.caltech.edu

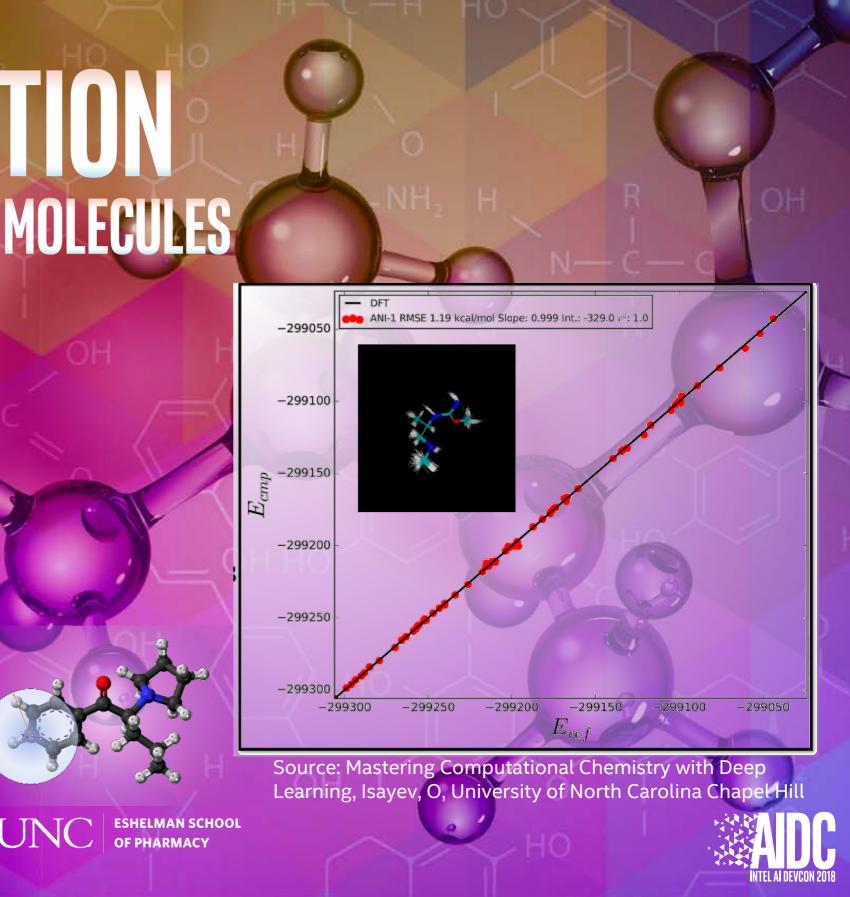
ILLINOIS



TRACKING ESTIMATION APPROXIMATING THE BEHAVIOR OF MOLECULES

- Predicting behavior of organic molecules
- Compute intensive Kohn-Sham Density-Functional Theory (DFT) equations
- Database of 20 million conformations
- Chemically accurate DL
- 10⁵ speedup; ~6x10⁻⁴ power reduction

OH



SEQUENCE MAPPING

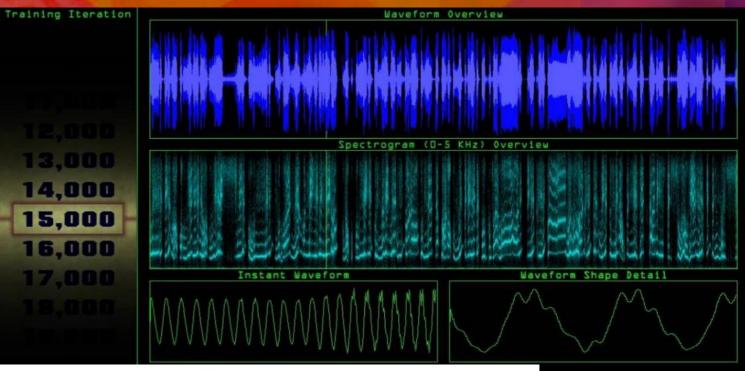
Creating output sequence based on context based, multidimensional, continuous input sequence

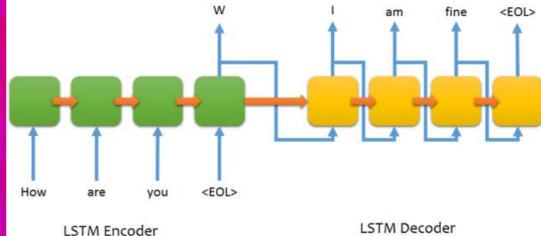
Applicable DL techniques: Neural Machine Translation (NMT)

Sequence-to-sequence transformation

Supervised learning:

Sequence examples tagging







SEQUENCE MAPPING CONTEXTUAL SPEECH GENERATION

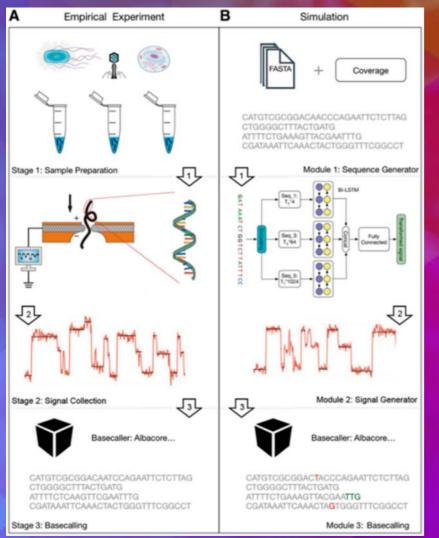
- Stephen Hawking device effective translation of cheek movements to cursor and mouse controls
- Machine Learning, multi-context
- Customized language models
- High accuracy at predicting syllables and words
- ACAT (Assistive Contextually Aware Toolkit) by Intel Labs
- Added Speech Synthesis



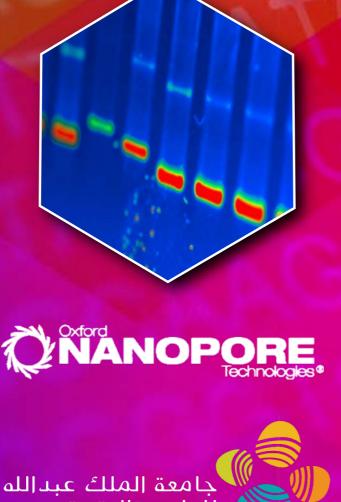
https://01.org/acat



SEQUENCE MAPPING **GENOMICS - NANOPORE SEQUENCING**



Yu Li et al.: DeepSimulator: a deep simulator for Nanopore sequencing.



للعلوم والتقنية King Abdullah University of Science and Technology

- DNA/RNA high TPT sequencing by Oxford Nanopore Tech
- **DeepSimulator mimics entire**
- Addressing repetitive regions

From noisy electrical waveforms, predicting sequence of ATCGs pipeline, similar to experimental



Rollout policy

Policy gradient

SPACE EXPLORATION

 Solution space too large for scientist trial-and-error
Lack of model to guide exploration

Applicable DL techniques: Reinforcement Learning (RL) Meta Learning (learning how to best learn) + previous methods to evaluate branches Unsupervised learning

uman expert positions

Source: https://medium.com/@karpathy/alphago-in-context-c47718cb95a5

Policy network

paip (a s)

RL policy network

Value network





Neural networ



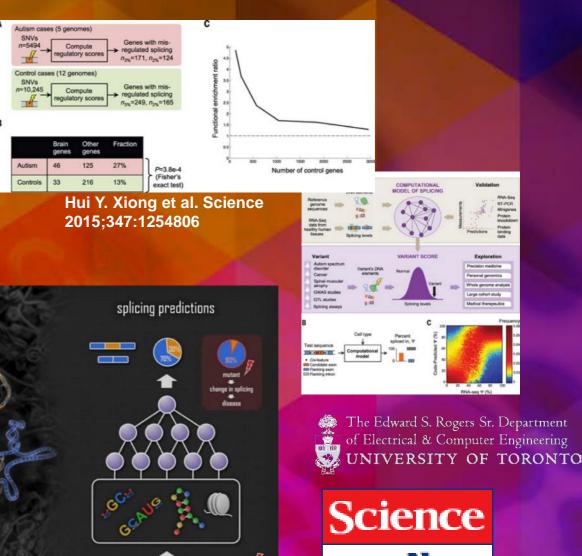
Self-play positions

Value network

 $v_{\theta}(s')$



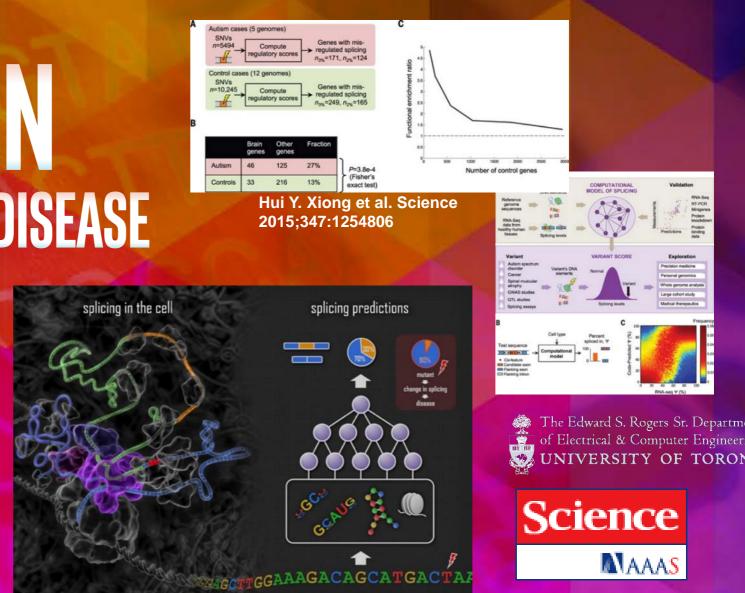
SPACE EXPLORATION **REVEALING THE GENETIC ORIGINS OF DISEASE**



- Ranking of genetic mutations based on how living cells 'read' DNA
- DL learns genetic instructions for proper splicing, protein production
- Evaluate mutations and likelihood of causing disease
- Facilitate discovery of unexpected genetic determinants of autism, cancer, spinal muscular atrophy

(H. Y. Xiong. et al.: The human splicing code reveals new insights into genetic determinants of disease, Science 347)

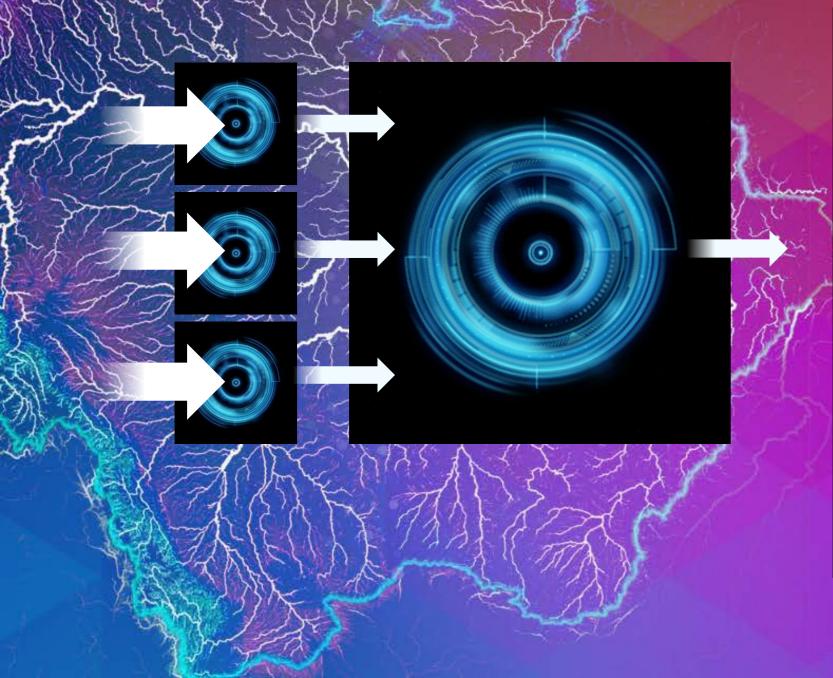
Challenge – which mutations to try?



- Finding preferred path in complex space : Neural Arch Search with **Reinforcement Learning** (by Zoph, B. and Le, Q. V.)
- "Use ML for ML Itself"



REFERENCE SCURATION



- Massive number of data sources
- Data curation: intelligent filtering at the source
- Combined learning of filtering functions & data analysis

Applicable DL techniques: Ensemble Learning: central plus **Distributed processing** Multiple ML techniques

Unsupervised Learning



FROM PAST/PRESENT TO THE FUTURE FROM PREDICTIONS TO TAKING ACTION

DIAGNOSTIC ANALYTICS

PRESENT

PREDICTIV

ANALYTICS

ANALYTICS CURVE



PAST

FUTURE

PRESCRIPTIVE

ANALYTICS

B GENERATIVE ANALYTICS



OUTLOOK: Challenges and opportunities

Address lack of theory and explainability
Understand limits of supervised & unsupervised learning
Update skillset of senior scientists

Fully utilize ML targeted 'solver' capabilities – "10⁴ factor"
Evolve from a dataset to tapping flowing phenomenon
Harness ML as a creative co-explorer



