VERMONT EPSCOR BREE

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UNIVERSITY OF VERMONT

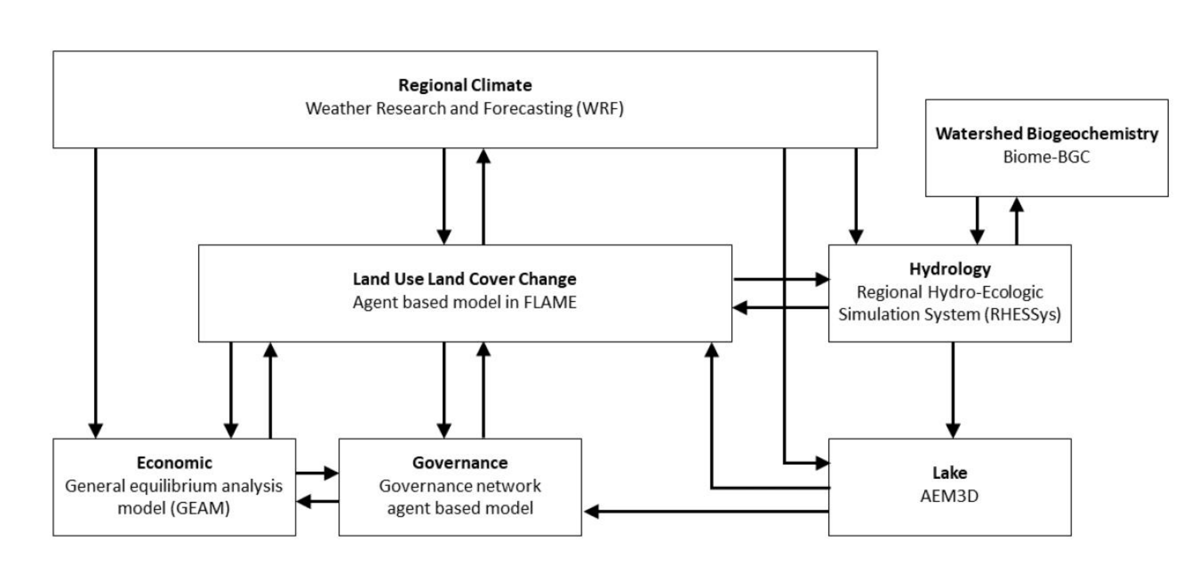
VERMONT EPSCOR BREE PROJECT

- EPSCOR: ESTABLISHED PROGRAM FOR STIMULATING COMPETITIVE RESEARCH
- **BREE**: BASIN RESILIENCE TO EXTREME EVENTS
  - 5 YEAR GRANT (ENTERING 5TH YEAR)
  - INVESTIGATING EFFECTS OF CLIMATE CHANGE, WEATHER, AND LANDUSE CHANGES ON THE STRENGTH AND FREQUENCY OF TOXIC ALGAE BLOOMS IN LAKE CHAMPLAIN
  - SCIENCE LEADS, POSTDOCS, AND GRADUATE STUDENTS MODEL GOVERNMENT NETWORKING, ECONOMIC FORECASTS, LANDUSE BEST PRACTICES, CLIMATE PREDICTIONS, WEATHER CYCLES, HYDROLOGY, AND LAKE DYNAMICS
  - WATERSHED INSTRUMENTATION AND NATIONAL DATABASES PROVIDE HISTORICAL DATA FOR USE IN CALIBRATION
  - ALL MODELS COMBINED INTO AN IAM (INTEGRATED ASSESSMENT MODEL) TO EXPLORE THE SCENARIOS DATASPACE
  - IAM RUN ON A COMBINATION OF LOCAL RESOURCES AND THE CHEYENNE PETAFLOP HPC COMPLEX
  - OVER 50 PEOPLE INVOLVED IN RESEARCH, SUPPORT, AND ADMINISTRATION

BREE
Basin Resilience to Extreme Events
in the Lake Champlain Basin

GRANT: NSF OIA 1556770

BREE COMPUTATIONAL COMPONENTS



- MODELED IN DIVERSE LANGUAGES AND ENVIRONMENTS
  - JAVA, C++, R, PYTHON, FORTRAN
  - ANYLOGIC, MASON, FLAME,
  - RHESSYS, SWAT, RCA/EFDC, AEM3D, WRF
- LOCAL DEVELOPMENT RESOURCES
  - LINUX REDHAT WORKSTATION
  - NVIDIA DGX-1 FOR GPU ACCELERATION
  - GITLAB, RSTUDIO, VSCODE
- WORKFLOW EXECUTED BY FRAMEWORK, DATA, AND QUEUE MANAGERS
  - PEGASUS, GLOBUS, HTCONDOR, PBS
- 2 STAFF MAINTAIN RESOURCES, AUTHOR THE WORKFLOWS, GENERATE DATA VISUALIZATIONS AND RUN THE IAM

BREE AND MACHINE/DEEP LEARNING

MACHINE/DEEP LEARNING PROVIDES POWERFUL TOOLS FOR MODELING COMPLEX SYSTEMS

BREE IS NO EXCEPTION

- SELF ORGANIZING MAPS FOR CLUSTERING DATA CATEGORIES
- PATTERN/IMAGE RECOGNITION FOR IDENTIFYING EVENTS
- AGENT BASED MODELING WITH EXPERIENTIAL LEARNING
- EMULATOR FUNCTION DEVELOPMENT TO ANALYZE COMPLEX IAM

UNAL "ZAK" SAKOGLU
UNIVERSITY OF HOUSTON - CLEAR LAKE

Computation of adaptive space filling curves for brain MRI classification

Unal "Zak" Sakoglu, Lohit Bhupati

Computer Engineering, University of Houston - Clear Lake, Houston, TX

I. INTRODUCTION

- Neuroimaging or brain image research has different techniques to study structural and functional imaging.
- Structural neuroimaging is for studying the structure of the nervous system.
- Functional neuroimaging is studying the functioning of the brain under different conditions, BOLD fMRI is a measure of neural activity.
- The aim of this work is to classify healthy controls vs patients by utilizing the differences in patterns of the fMRI brain activation maps, and use better features via adaptive space-filling curves.
- fMRI images are stored in .nii format. These are acquired in three-dimension (3D) over time so the fMRI has 4 dimensions.
- The basic element in the 3D image is known as a voxel (volume element).

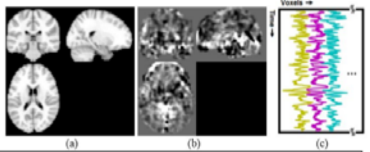
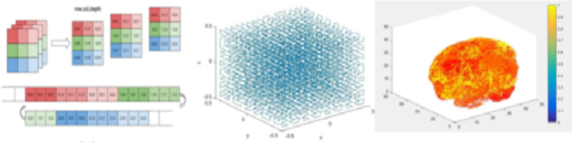


Figure 1 Three views of a structural T1 MRI dataset (a), and an fMRI brain activation map (b), which is computed from fMRI volumes taken at multiple time-points. Conventionally, fMRI da-taset voxels are ordered using linear ordering trajectory into rows of a matrix, as a result, a matrix of *time× voxels* is generated for further analyses (c).

II. 3D to 1D ORDERING & SPACE FILLING CURVES

Why Ordering? 3D MRI data need to be converted to 1D for further analyses:
In this work the following orderings are used.

- Linear ordering (conventional, pre-determined)
- Hilbert ordering (pre-determined)
- Proposed adaptive space filling curve ordering, **is a modified TSP problem, NP-hard**, exponential-time O(e^N) computation, where N is ~ 156K–264K [Sakoglu-1]



(a) (b) (c)

Figure 2 (a) Linear ordering (b) Hilbert ordering (c) Proposed optimal space filling curve ordering

III. METHODS

- **Method-1**
  - The average brain map using all participants is calculated. Then the mean brain map is masked using the mask and the non-brain region is removed. The masked activation map is zero masked to apply Hilbert curve of N = 64x64x64 which is pre-generated and this predetermined Hilbert curve is mapped on the mean activation map.
  - Using the Hilbert curve trajectory the 3D activation map are converted to 1D.
  - Using an absolute threshold we remove all the value below the limit from the 1D brain map and also keeping track of the index where the values are removed.
  - The indexes as in the average brain map are removed from all the brain maps, which stimulates that all the value in a column same region for all the participants.
  - As the number of attributes is too high binning is performed. After the 1D conversion the length of the array is around 262,144, so using different bin sizes the data is downsized.
  - The T test is used and with different p values, the important features are selected. These selected features are further used for the classification of the data.
- **Method-2**
  - There is no mean activation map calculation.
  - Each participant is masked and then each ordering is applied accordingly and then converted to 1D.
  - Down sampled using binning and feature selection using *t* statistics and sequential forward selection techniques.
  - Different classification techniques are used and also passed through a deep learning model.

IV. RESULTS

- Hilbert based classification achieved slightly better classification accuracy than that of SFC (approximately 76% vs 75%) when utilizing sequential forward search.
- When no feature selection was used, the SFC provided a slightly better accuracy for most of the classification algorithms utilized and also SFC has the best result when applied the cost function.
- Cost function (root mean square of signal differences in orderings)

Linear Ordering: 375,898.9 (156K voxels). Hilbert Ordering: 353,553.4 (156K voxels).

SFC Ordering: 33,971.3 (156K voxels) an order of magnitude less!!!! But finding the curve took weeks!!!

Tables 1 – 3 below summarize classification results with different algorithms, feature selection, and ordering methods.

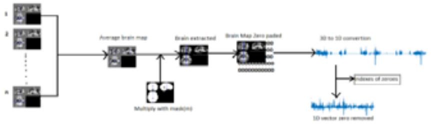


Figure 3 Part (A) of method-1

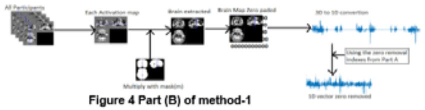


Figure 4 Part (B) of method-1

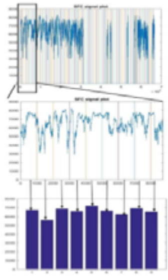


Figure 5 SFC plot

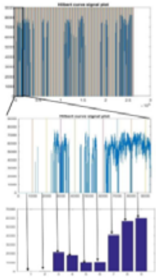


Figure 6 Hilbert plot

Table 1 Classification of Schizophenia Results

Methodology	Bin Size	Classification Accuracy with different algorithms on MCIC data for 100 iterations					
		Num. of Attributes	Voting Algorithm	SVM	Gaussian	Random Forest	Perceptron
Downsized brain	N/A	2146	49.90%	49.80%	50.00%	49.40%	46.50%
Linear	100	1536	47.00%	46.70%	47.40%	46.10%	49.40%
Hilbert	100	2622	62.30%	63.30%	55.40%	60.10%	67.00%
SFC	100	622	62.30%	65.40%	58.60%	61.20%	64.60%

Table 3 Classification of Cocaine Addiction Results

Classification of cocaine addiction using multi-layer perceptron		
About the Data	Hilbert	Linear
bin size 100 and p < 0.05	77.30%	75.30%
bin size 100 and p < 0.03	77.00%	66.40%
bin size 200 and p < 0.05	72.50%	69.80%
bin size 200 and p < 0.03	74.50%	70.00%

Table 2 Classification of Schizophenia Results, SFS

Classification Accuracy table following Sequential forward selection on MCIC dataset							
Ordering	Bin size	Number of Attributes in the set	Number of Attributes used for Classification	Iterations	Algorithm	Highest accuracy	No. of attributes that achieve the highest accuracy
SFC	100	667	30	100	SVC	72.1%	25
Hilbert	100	2622	30	100	SVC	73.2%	30
Linear	100	1536	30	100	SVC	49.9%	14
SFC	100	667	100	100	SVC	74.6%	100
Hilbert	100	2622	100	100	SVC	76.8%	100
Linear	100	1536	100	100	SVC	50%	27

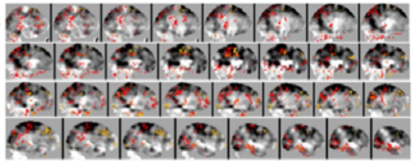


Figure 7 Sagittal view of back-mapped features of SFC on the 3D brain MRI (bin size=100, 100 attributes).

V. CONCLUSIONS

- Hilbert based classification achieved slightly better classification accuracy than that of SFC (approx. 76% vs 75%) when utilizing sequential forward search.
- When no feature selection was used, the SFC provided a slightly better accuracy for most of the classification algorithms utilized and also SFC has the best result when applied the cost function.
- This is a computationally intense problem (finding the SFC, applying the machine learning algorithms,…)

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ACKNOWLEDGMENETS

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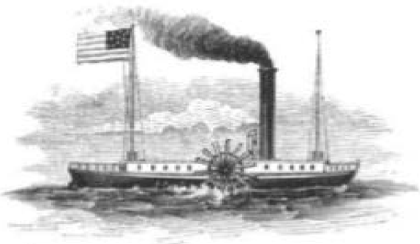
Possible ?

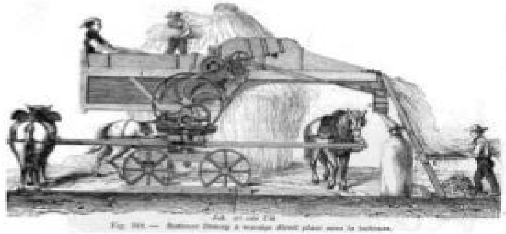
AI/ML/DL (CON'T)

The 1st Industrial Revolution (Mechanization)

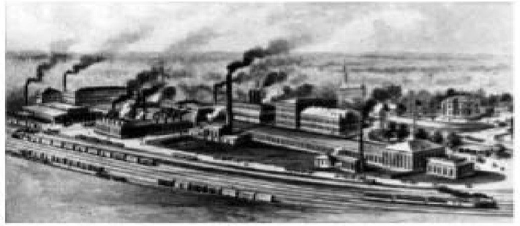
- No concrete start date for the 1st Industrial Revolution.
- After 1760 – these changes were noticeable first in England when steam engine was invented by James watt.
- Then took place in the United States, Belgium, and France.



Changed Noticed After 1st Industrial Revolution:



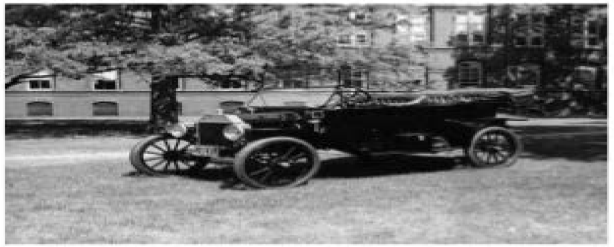
Agricultural Revolution

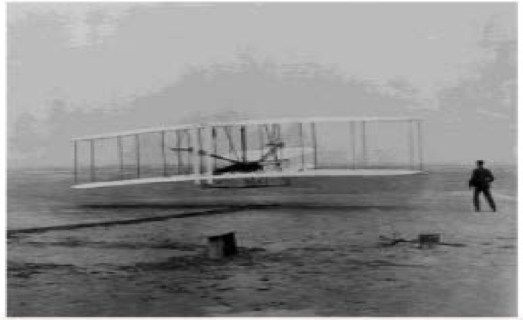


Development of Factories

The 2nd Industrial Revolution

The second Industrial Revolution took place between about 1870 and 1960. Saw the spread of the Industrial Revolution to places such as Germany, Japan, and Russia.





- Electricity became the primary source of power for factories, farms, and homes.
- Mass production, particularly of consumer goods.
- Use of electrical power. (electric lights, radios, fans.)

The 3rd Industrial Revolution

Nearly a century later, in the second half of the 20th century, a third industrial revolution appeared with the emergence of a new type of energy whose potential surpassed its predecessors: **Nuclear energy.**

This revolution witnessed the **rise of electronics** with
- The transistor and microprocessor.
- Telecommunications.
- Computers.
- Development of the Internet, fast communications.

The 4th Industrial Revolution

And we are now starting number 4.0. It is changing…

The way we work, buy and sell things	The way we travel	The way we live
		

- The Fourth industrial Revolution is unfolding before our eyes where we are. This is the first industrial revolution rooted in a new technological phenomenon – '**digitalization**' rather than in the emergence of a new type of energy.
- The Fourth Industrial Revolution is being driven by **extreme automation and extreme** connectivity. The sectors which is taking us towards global "Digitalization" are -

AI/ML/DL (CON'T)

AI and Deep Learning

As Baidu and Alibaba fight over the Chinese marketing for smart speakers, Amazon and Google do so in the West and the voice-interface is coming to everything. It's a more radical shift than many consumers and businesses estimate. The consumer robots will roll out in the 2030s.

How big?

- Bank of America–Merrill Lynch predicts by 2020:
  - $153 billion market for AI-enabled technology, including:
    - $83 billion for robotics
    - $70 billion for AI-based analytics
  - With an estimated $14-33 trillion creative disruption impact annually
    - $8-9 trillion in cost reductions in manufacturing and health care
    - $9 trillion cuts in employment costs due to AI-enabled automation
    - Manufacturing labor costs cut 18-33%
    - $1.9 trillion in efficiency gains due to autonomous drones & cars
    - Productivity boosted 30% in many industries
    - 47% of jobs have the potential to be automated

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7

SWEEPING ACROSS INDUSTRIES

Internet Services | Medicine | Media & Entertainment | Security & Defense | Autonomous Machines

Internet Services
- Image/Video classification
- Speech recognition
- Natural language

Medicine
- Cancer cell detection
- Diabetic grading

Media & Entertainment
- Video captioning
- Content based search

Security & Defense
- Face recognition
- Video surveillance

Autonomous Machines
- Pedestrian detection
- Lane tracking
- Recognize

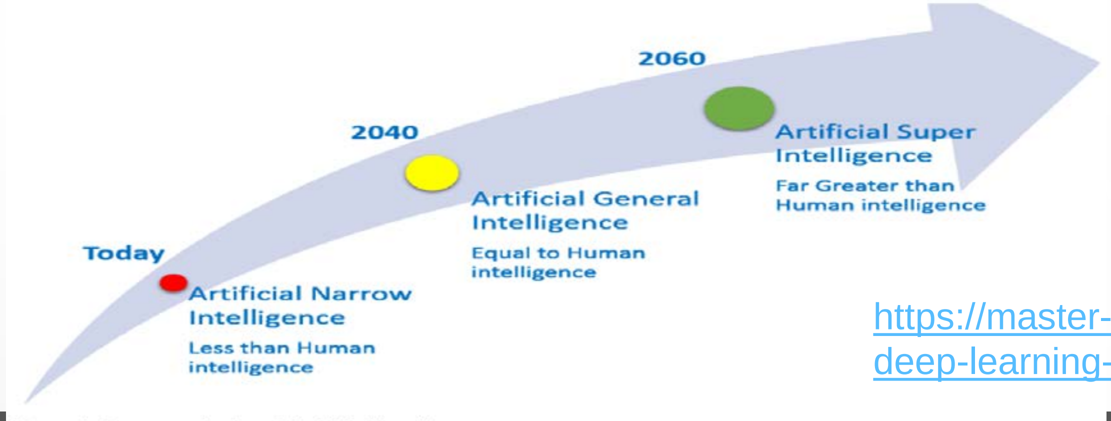
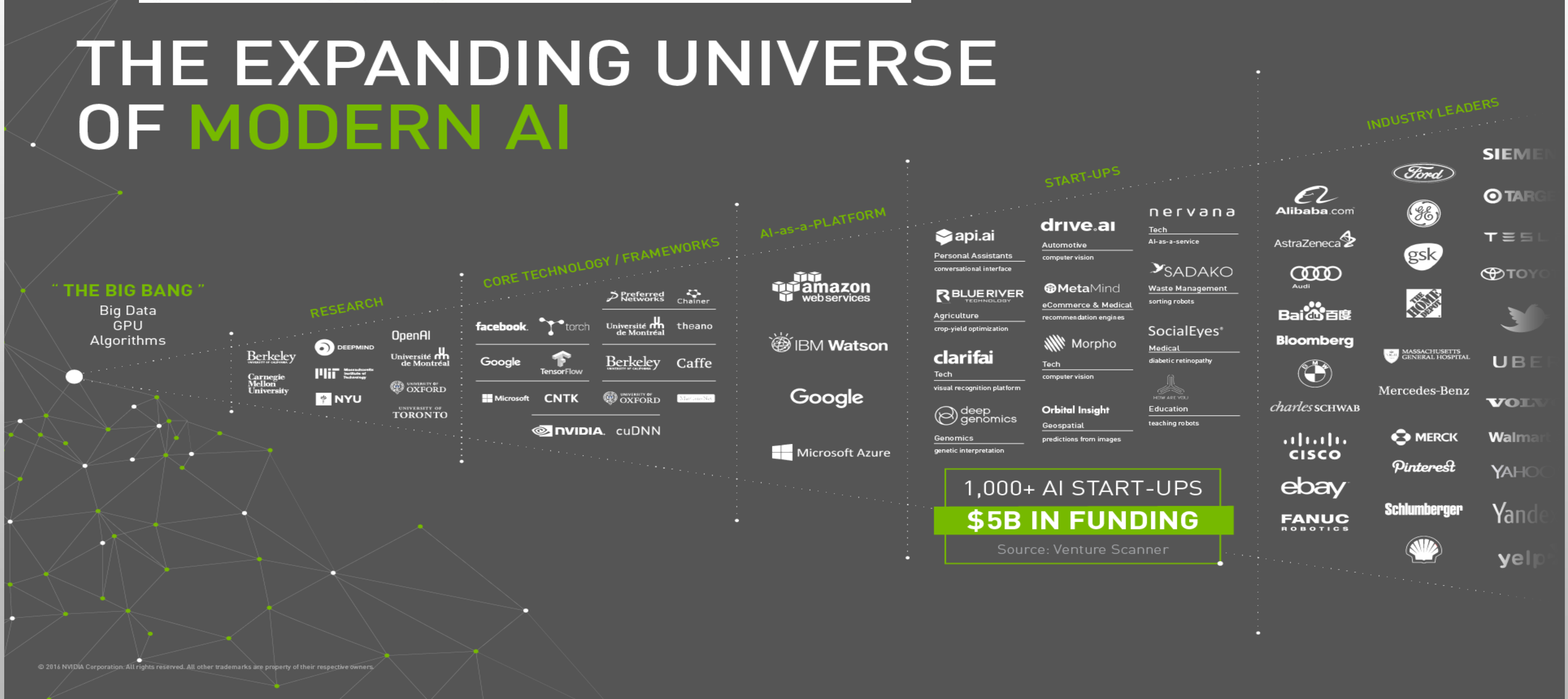
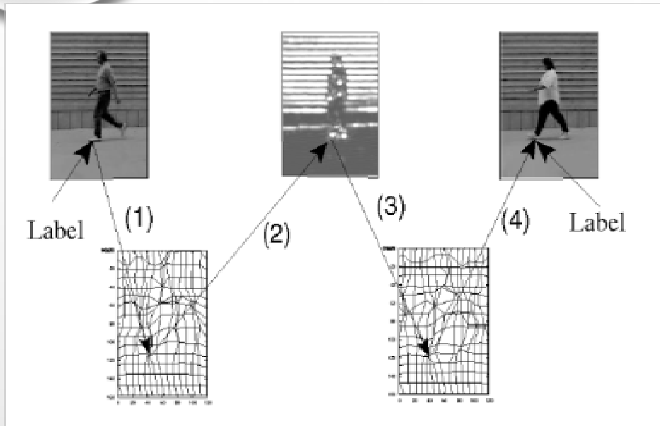


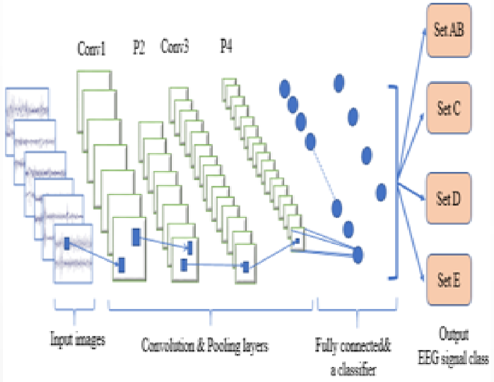
Figure 4: Future evolution of Artificial Intelligence

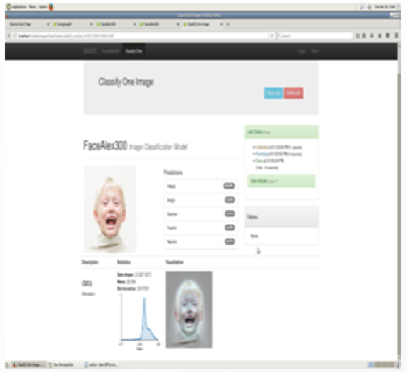
https://master-iesc-angers.com/artificial-intelligence-machine-learning-and-deep-learning-same-context-different-concepts/

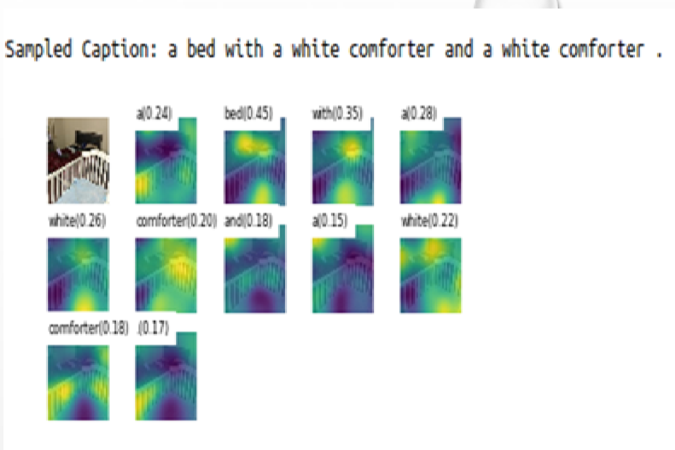


Examples of Student from UALR Engagement in AI/ML/DL Research









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https://www.researchgate.net/profile/Mariofanna_Milanova

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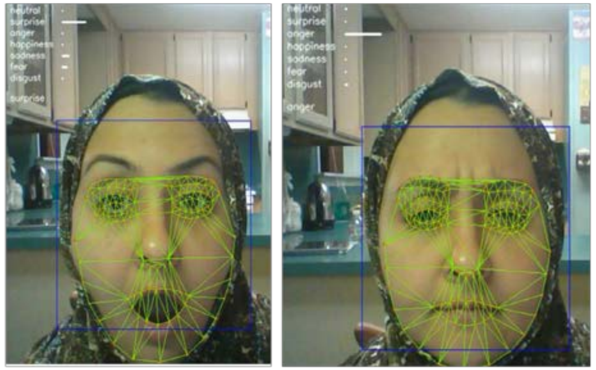


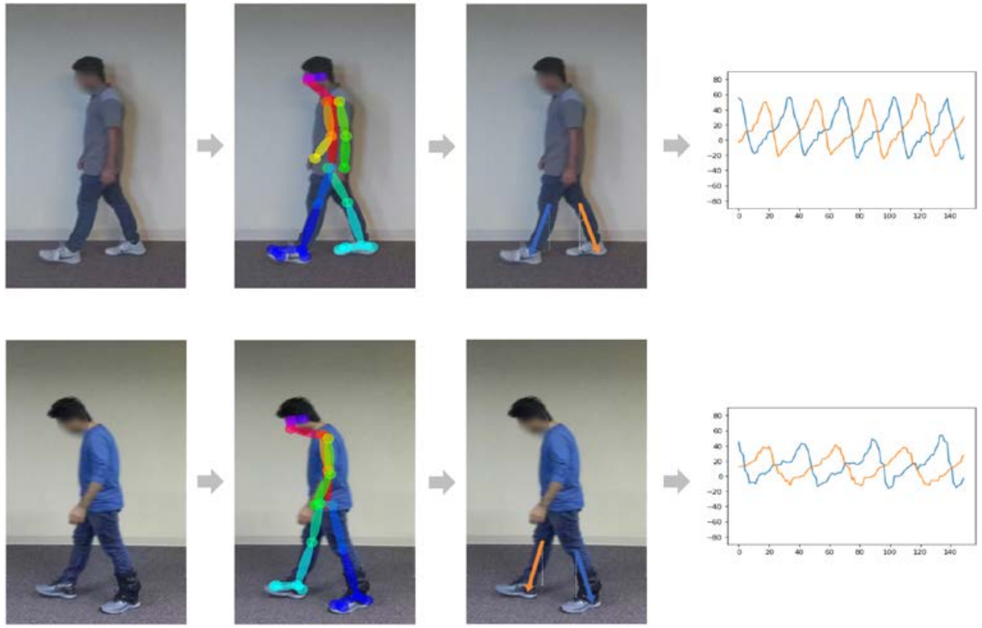
Fig. a. and b. Emotion Recognition with probability distribution

Fig a. and b. Improved feature detection over standard practices, shown in green

Jetson Community Projects
https://developer.nvidia.com/embedded/community/jetson-projects

https://www.nvidia.com/en-us/autonomous-machines/robotics/

AWS Educate Platform, https://www.youtube.com/watch?v=OxQUo3kwTEA



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Fundamentals of Multiple Data Types (MDT)
Natural Language Processing

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- Ph.D. candidate at Kansas State University
  - Research Area: High Performance Computing (Improving the Performance of the Slurm Workload Manager)
- Instructor (2008 – 2012), TA & RA (2014 – Current)
- A Cyberinfrastructure team member at New Mexico State University (Jan 2017 – Jan 2019)
- XSEDE Student Campus Champion (2017 – Current)
- XSEDE Fellow (2018 – 2019)

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