Development of Adaptive Computational Algorithms for Manned and Unmanned Flight Safety

Colin P. Elkin, PhD Candidate

Committee Chair: Dr. Vijay Devabhaktuni
Committee Member: Dr. Mansoor Alam
Committee Member: Dr. Ahmad Javaid
Committee Member: Dr. Devinder Kaur
Committee Member: Dr. Weiqing Sun
Committee Member: Dr. Lawrence Thomas

Department of EECS, The University of Toledo

November 5th, 2018

Overview

THE UNIVERSITY OF TOLEDO 1872

Overview: Airline Safety Issues

- Important human factor: high mental workload
- Pilots work under high levels of multitasking
- Risk of mental overload

Overview: Airline Safety Issues

- Some automation have been implemented to ease the burden of overload
- Can result in mental underload
- Impacts ability to react to sudden events
- Example: driver overload vs. underload

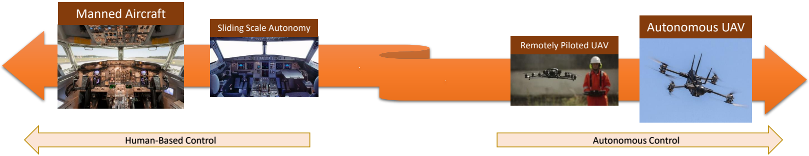
THE UNIVERSITY OF TOLEDO 1872

Overview: Airline Safety Issues

- Flight safety has improved, but goal is always to achieve near 100% safety
- Goal: examine human aspects of safety by optimal cognitive workload

UAVs in Shared Airspace: a New Frontier

- Before 2012: mostly used by hobbyists and military
- Today: broader and more commercial applications
- Need for UAVs to integrate into shared airspace
- Thus, UAV safety will be a growing concern



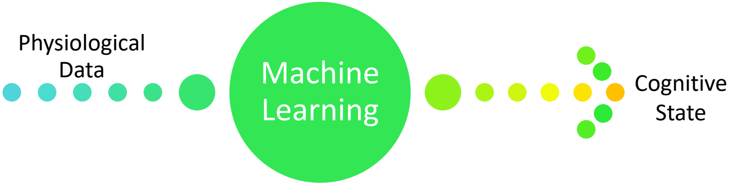
Research Objectives and Process

Manned	Unmanned
Identify ML techniques for cognitive workload	Examine ML techniques for UAV data prediction
Analysis of alternatives	Dynamic ML switching technique
Adaptive ML selection technique	Smoother autonomous path planning
Alert pilots of future overload or underload	

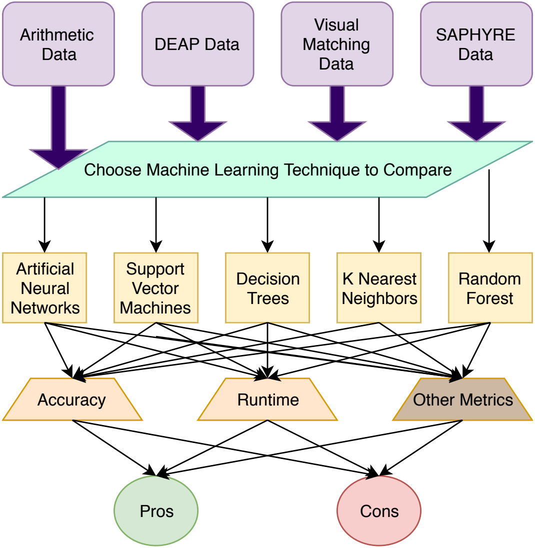
Cognitive Workload Assessment

Problem Statement

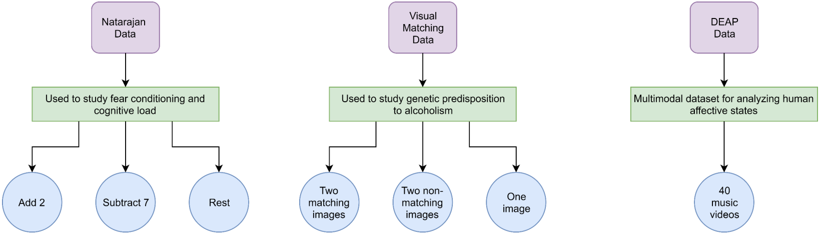
The aim of this phase of the research is to perform an analysis of alternatives of the machine learning approaches that are currently used for assessing cognitive workload.



Experimental Process



Approach: Data Acquisition

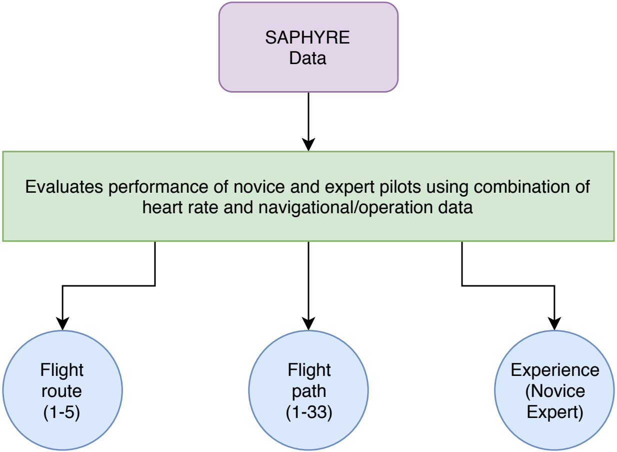


Input:
EDA

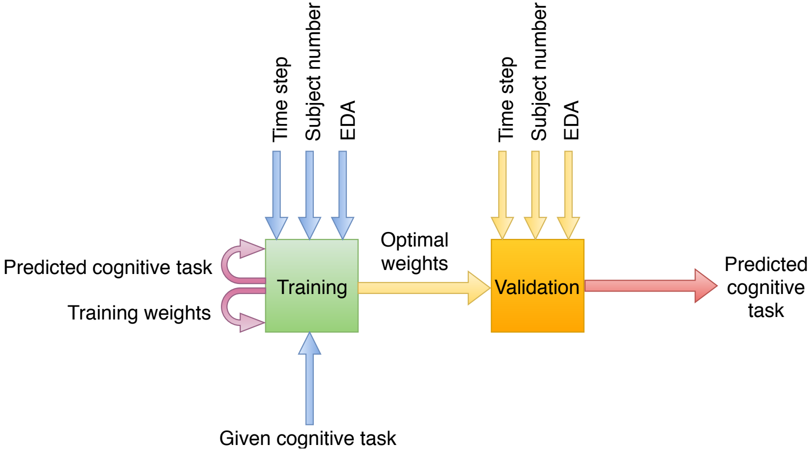
Input:
EEG

Input:
EEG

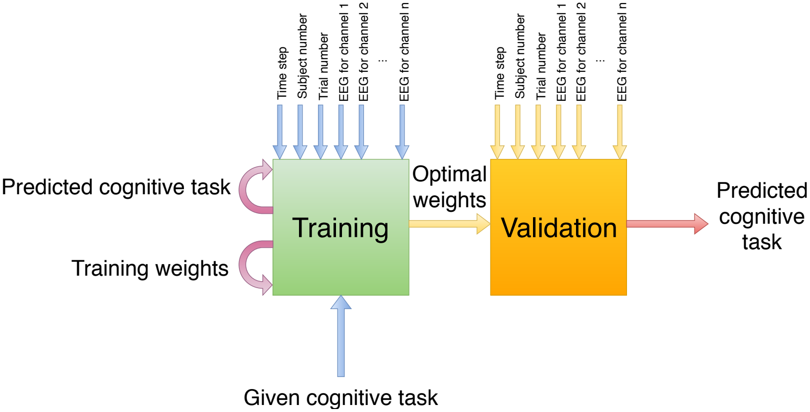
Approach: Data Acquisition II



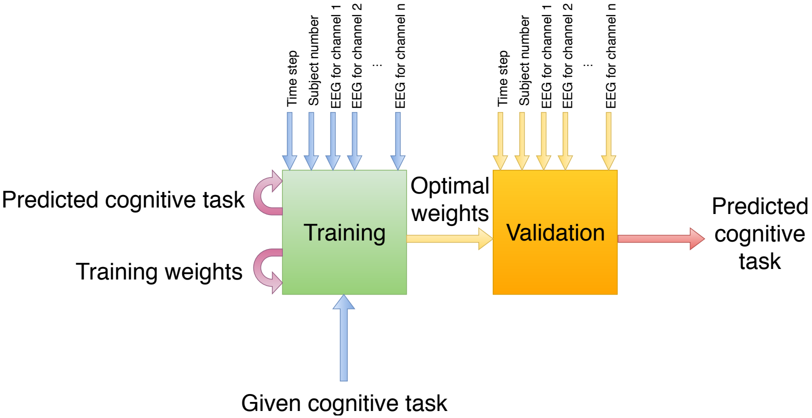
Approach: Data Acquisition - Arithmetic



Approach: Data Acquisition - Visual Matching



Approach: Data Acquisition - DEAP

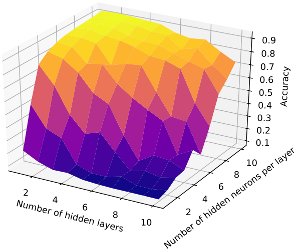


Experimental Setup

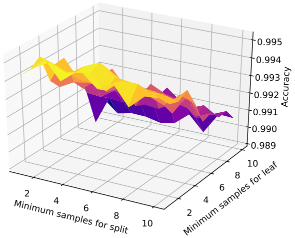
- Programmed in Python using scikit-learn toolkit for built-in ML tools
- Tested under multiple method-specific parameters
- Used iterative combinations of other parameters to show how results vary in three dimensions
- Results presented as averages of 10 independent experiments

SAPHYRE Results

ANN Accuracy

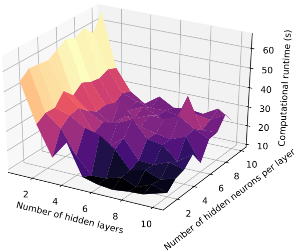


RF Accuracy

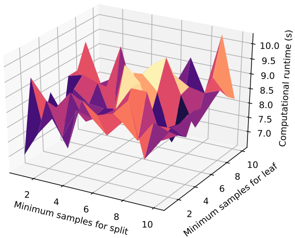


SAPHYRE Results II

ANN Runtime



RF Runtime



Overview of ML Analysis

Technique	Arithmetic	DEAP	Visual Matching	SAPHYRE
ANN SGD	Wide range of results	Best in most metrics	Best runtime	Widest range of results
ANN LBFGS	Wide range of results	Best in most metrics	Nothing noteworthy	Highest max. runtime
KNN Uniform	Most susceptible to overfitting	Worst max. runtime	Overfitting	Nothing noteworthy
KNN Distance	Most susceptible to overfitting	Second worst max. runtime	Overfitting	Nothing noteworthy
SVM Linear	Worst in all metrics	Worst in most metrics	Nothing noteworthy	Nothing noteworthy
SVM RBF	Worst maximum runtime	Worst runtime	Worst runtime	Nothing noteworthy
DT Gini	Best in all metrics	Nothing noteworthy	Best in most metrics	Nothing noteworthy
DT Entropy	Best in all except runtime	Nothing noteworthy	Second best in most metrics	Best runtime
RF Gini	Second best in most metrics	Nothing noteworthy	Overfitting	Best max. accuracy
RF Entropy	Third best in most metrics	Nothing noteworthy	Overfitting	Best in most metrics

Overview of ML Analysis

Technique	Arithmetic	DEAP	Visual Matching	SAPHYRE
ANN SGD	Wide range of results	**Best in most metrics**	Best runtime	Widest range of results
ANN LBFGS	Wide range of results	**Best in most metrics**	*Nothing noteworthy*	Highest max. runtime
KNN Uniform	Most susceptible to overfitting	Worst max. runtime	Overfitting	*Nothing noteworthy*
KNN Distance	Most susceptible to overfitting	Second worst max. runtime	Overfitting	*Nothing noteworthy*
SVM Linear	Worst in all metrics	Worst in most metrics	*Nothing noteworthy*	*Nothing noteworthy*
SVM RBF	Worst maximum runtime	Worst runtime	Worst runtime	*Nothing noteworthy*
DT Gini	**Best in all metrics**	*Nothing noteworthy*	**Best in most metrics**	*Nothing noteworthy*
DT Entropy	**Best in all except runtime**	*Nothing noteworthy*	**Second best in most metrics**	Best runtime
RF Gini	Second best in most metrics	*Nothing noteworthy*	Overfitting	**Best max. accuracy**
RF Entropy	Third best in most metrics	*Nothing noteworthy*	Overfitting	**Best in most metrics**

Next Steps

Can identify which techniques work best with different datasets based on their attributes

Next step: adaptive algorithm that chooses an ML technique based on characteristics of the data

Big picture: Early detection of pilot's cognitive overload or underload

Adaptive Workload Prediction - Background

Dataset	No. Inputs	No. Classifications	Best Method	Optimal Parameters
Arithmetic	3	5	DT	gini, 9 for split, 2 for leaf
Visual Matching	66	3	DT	gini, 9 for split, 2 for leaf
DEAP	42	40	ANN	SGD, 7 neurons, 2 layers
SAPHYRE	16	165	RF	entropy, 7 for split, 10 for leaf

Adaptive Workload Prediction - Background

Dataset	No. Inputs	No. Classifications	Best Method	Optimal Parameters
Arithmetic	Lo	Lo	DT	gini, 9 for split, 2 for leaf
Visual Matching	Hi	Lo	DT	gini, 9 for split, 2 for leaf
DEAP	Hi	Hi	ANN	SGD, 7 neurons, 2 layers
SAPHYRE	Lo	Hi	RF	entropy, 7 for split, 10 for leaf

Adaptive Algorithm - Single Selection

```
train_in, val_in, train_out, val_out ← all possible input and output data
if number of output classifications < 20 then
    create DT classifier
else
    if number of inputs > 20 then
        create ANN classifier
    else
        create RF classifier
    end if
end if
train selected classifier
for all validation time steps do
    get validation accuracy for all time steps evaluated thus far
end for
return val_accuracy, method, runtime, train_accuracy
```

Algorithm 1: Pseudocode of single selection process.

Adaptive Algorithm - Dynamic Selection

```
train_in, val_in, train_out, val_out ← all possible input and
output data
create and train ANN, DT, and RF classifiers
if number of output classifications < 20 then
    select DT
else
    if number of inputs > 20 then
        select ANN
    else
        select RF
    end if
end if
for all validation time steps do
    get validation accuracy from selected method for all com-
    pleted time steps
    if accuracy is lower than that of another method then
        select method with highest accuracy
    end if
end for
return  val_accuracy, method, runtime, train_accuracy
```

Algorithm 2: Pseudocode of dynamic selection process.

Experimental Setup

- Programmed in Python using scikit-learn toolkit for built-in ML tools
- Tested per dataset, per algorithm, and per validation ratio (25%, 66%)
- Results presented as averages of 10 independent experiments

Single Selection Results

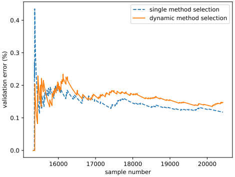
Metric	Arithmetic	Visual Matching	SAPHYRE
Training Accuracy	.999	.967	.995
Validation Accuracy	.999	.902	.989
Runtime (s)	12.1	36.5	129

Dynamic Selection Results

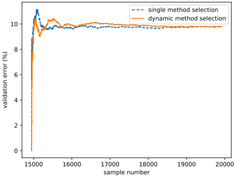
Metric	Arithmetic	Visual Matching	SAPHYRE
RF Train. Accuracy	.998	.845	.995
DT Train. Accuracy	.999	.974	.997
ANN Train. Accuracy	.444	.724	.161
Validation Accuracy	.999	.902	.991
Runtime (s)	134	147	241

Dynamic Selection Results per Sample - 25% Validation

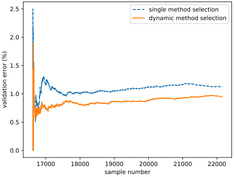
Arithmetic data



Visual matching data

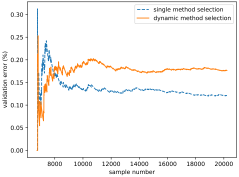


SAPHYRE data

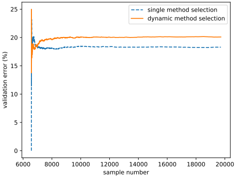


Dynamic Selection Results per Sample - 66% Validation

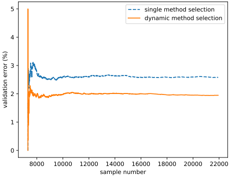
Arithmetic data



Visual matching data

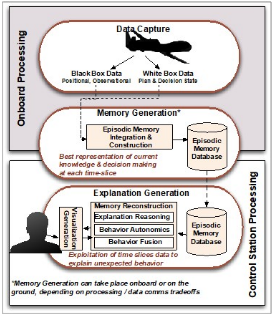


SAPHYRE data



Autonomous UAV Behavior

- Autonomous UAV behavior can be surprising to operators
- Need to improve transparency and understandability of autonomous behavior
- Also a need to reduce surprises from the start with improved predictions to weigh against outcomes



Problem Statement

The aim of this phase of the research is to use machine learning and data fusion to enhance the prediction of UAV behavior and explain the unpredictable.

Inclusion of Data Fusion

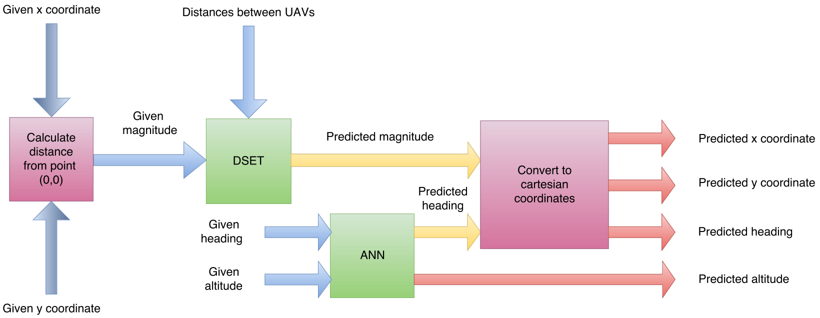
Combining multiple types of data improve prediction accuracy

Dempster-Shafer Evidence Theory (DSET) is a useful type of data fusion, can handle uncertainty

Previous research has shown that UAV sensors are not always accurate

Therefore, this phase implements DSET for sensor fusion in UAV data prediction

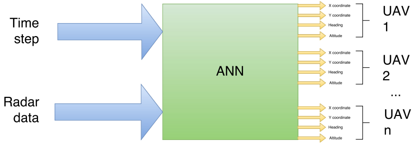
Proposed ANN+DSET Algorithm



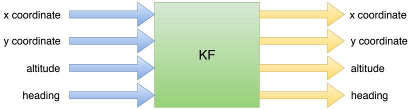
Experimental Setup

- Programmed in MATLAB
- Evaluated on a dataset of six UAVs over 695 seconds leading up to a crash
- Compared against a standard ANN to test the advantages/disadvantages of including DSET-based sensor fusion
- Also compared against Extended Kalman Filter and Unscented Kalman Filter
- Results given as the average of 10 independent trials for consistency

Methods to Compare



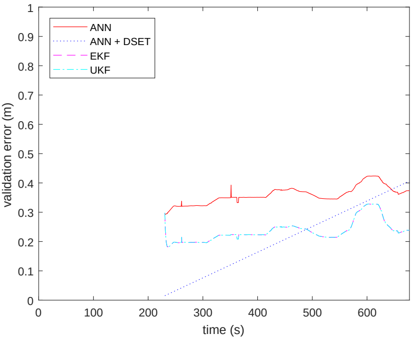
- Multi-layer Perceptron (MLP)
- Used for regression rather than classification
- Trained with Ant Colony Optimization
- No explicit data fusion



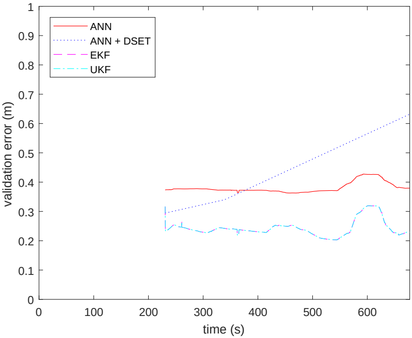
- Extended Kalman filter (EKF) and unscented Kalman filter (UKF)
- Uses equations derived from UAV dynamic models
- Differ from one another in amount of linearization involved

Comparison Results

One UAV at a time (average)



All UAVs evaluated together



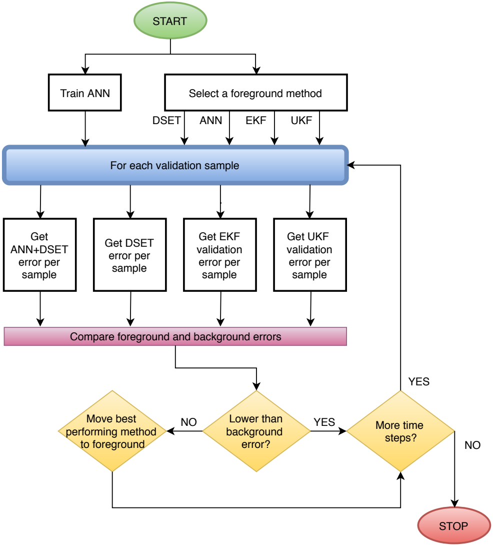
Next Steps

Can identify which techniques work best at different points in time

Next step: adaptive algorithm that chooses an a technique based on which is most accurate at a point in time

Big picture: Autonomous UAV behavior is easier to predict

Adaptive Trajectory Prediction

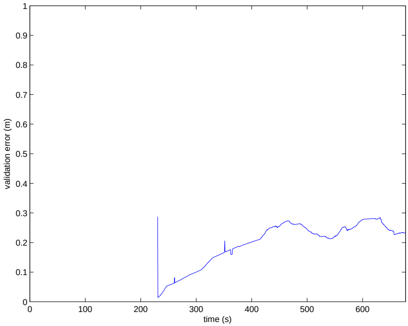


Experimental Setup

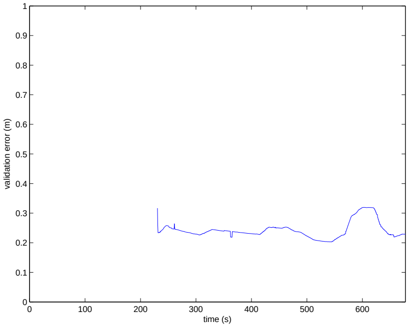
- Programmed in MATLAB
- Evaluated on a dataset of six UAVs over 695 seconds leading up to a crash
- Results given as the average of 10 independent trials for consistency

Comparison Results

One UAV at a time (average)



All UAVs evaluated together



Publications

[1] C. Elkin, B. Marinier, A. Javaid, D. Kaur, V. Devabhaktuni, and J. Zaientz, "Computational approaches for optimal manned and unmanned flight safety: a survey," Information Sciences (Under preparation)

[2] C. Elkin, B. Marinier, A. Javaid, D. Kaur, V. Devabhaktuni, and J. Zaientz, "Prediction of unmanned aerial vehicle behavior through a combination of Dempster-Shafer and artificial neural network sensor fusion," Expert Systems with Applications (Under revision)

Publications II

[3] C. Elkin and V. Devabhaktuni, "Analysis of Alternatives for Neural Network Training Techniques in Assessing Cognitive Workload," In: 9th International Conference on Applied Human Factors and Ergonomics (AHFE 2018). Orlando, FL, (2018)
[4] C. Elkin, S. Nittala, and V. Devabhaktuni, "Fundamental Cognitive Workload Assessment: A Machine Learning Comparative Approach," In: 8th International Conference on Applied Human Factors and Ergonomics (AHFE 2017). Los Angeles, CA, pp. 275-284 (2017)

THE UNIVERSITY OF TOLEDO 1872

Future Publications

Type	Publication/Contribution
Conference Paper	Adaptive machine learning approach for assessing cognitive workload.
Journal Paper	Enhancing human-driven flight safety through early detection of cognitive overload.
Conference Paper	Adaptive machine learning system for enhanced UAV path prediction.
Journal Paper	Improving unmanned flight safety through adaptive machine learning of trajectory estimation.

Conclusions

- Flight safety is examined from ML viewpoint for both manned and unmanned flight
- Compared different ML techniques for assessing cognitive workload from physiological and subjective data
- Data fusion using DSET was applied to autonomous UAV prediction and compared to ANN and KF
- Adaptive algorithms were developed that select ML technique based on data attributes and time steps
- Flight safety can be improved through early detection of cognitive workload and better understanding of autonomous UAV behavior

Future Work

- More cognitive workload datasets, including remote UAV pilots
- CW prediction by regression; UAV prediction by classification
- Additional data fusion techniques
- Early prediction of crossover points in adaptive techniques

Acknowledgements

- Dr. Vijay Devabhaktuni
- Drs. Alam, Javaid, Kaur, Sun, and Thomas
- All attendees here today
- Hem Regmi, Sai Nittala, and Mitchell Voyantzis
- Colleagues at NE 2042
- Friends and family, near and far

Thank you

Any Questions?