DETC2013-13155

A Privacy Preserving Data Mining Methodology for Dynamically Predicting Emerging Human Threats

Tuesday, August 6th, 2013

Gautam Manohar & Conrad S. Tucker

{gautam.atulya@gmail.com, ctucker4@psu.edu, }

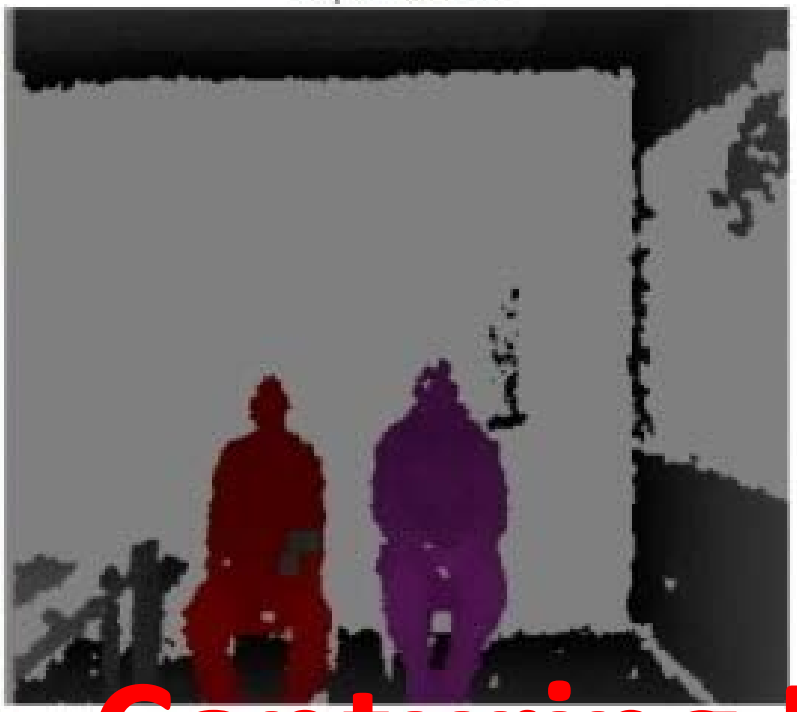
Presentation Overview

- Research Motivation and Background
- Methodology
  - The Knowledge Discovery process
  - Data Acquisition and Storage
  - Data Mining Predictive Model Construction
  - Result Interpretation and Output
- Application Case Study
- Results and Discussion
- Conclusion and Path Forward

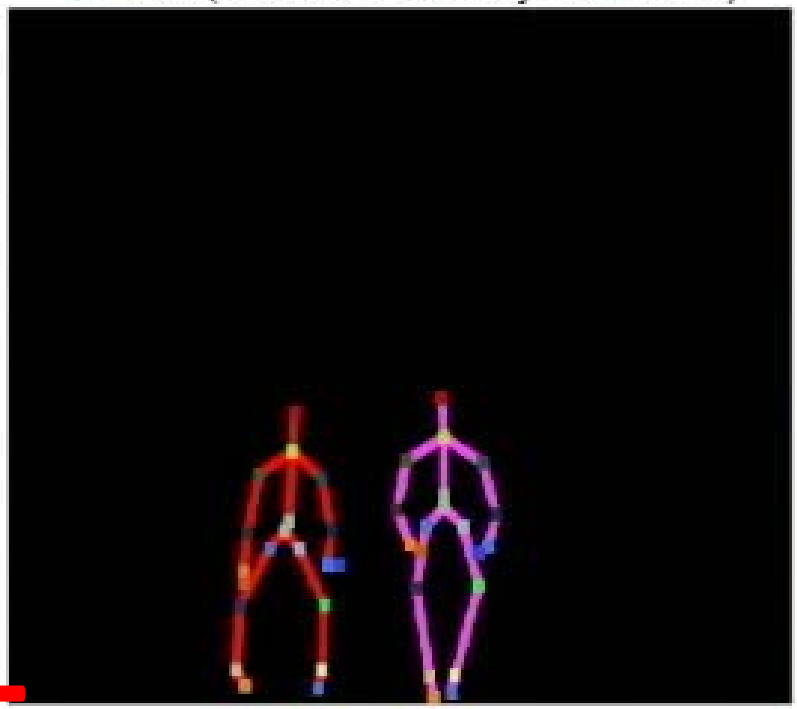
RESEARCH MOTIVATION

Motivation

Depth Stream



Skeleton (rendered if full body fits in frame)



Capturing Emergence

30 fps

Motivation and Background

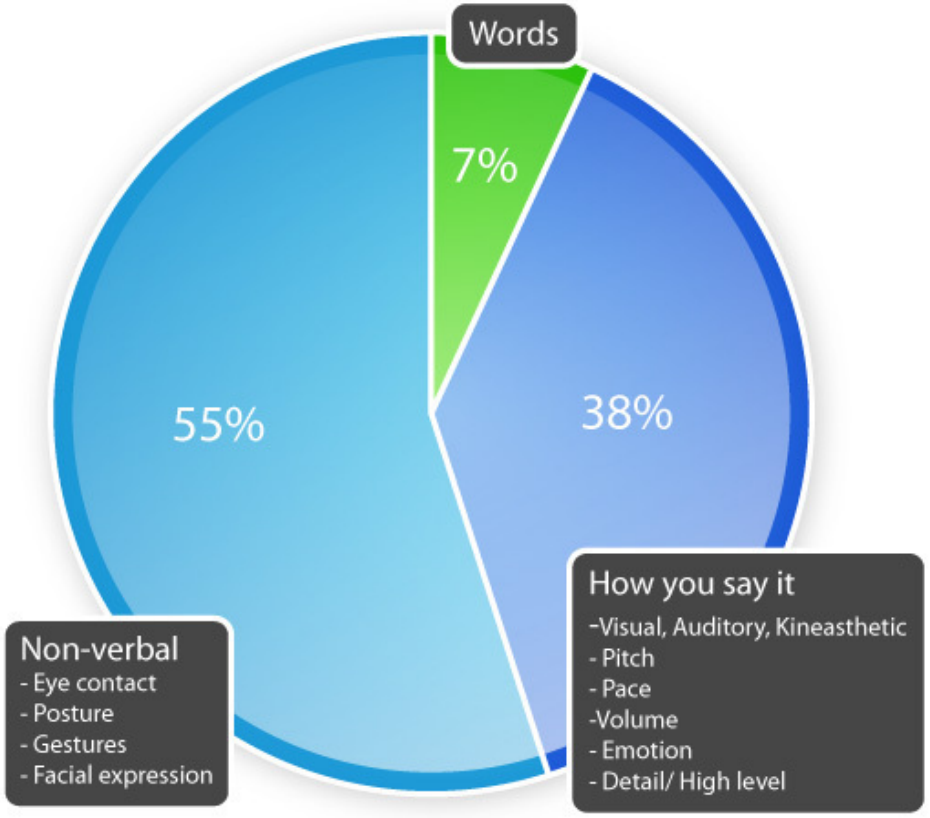
- Existing systems are passive and more useful for post-incident analysis.

- Privacy issues with most existing systems become a hindrance in public use (I.e. the need to preserve **Personally Identifiable Information (PII)**)

Why Individual Body Movement Data?

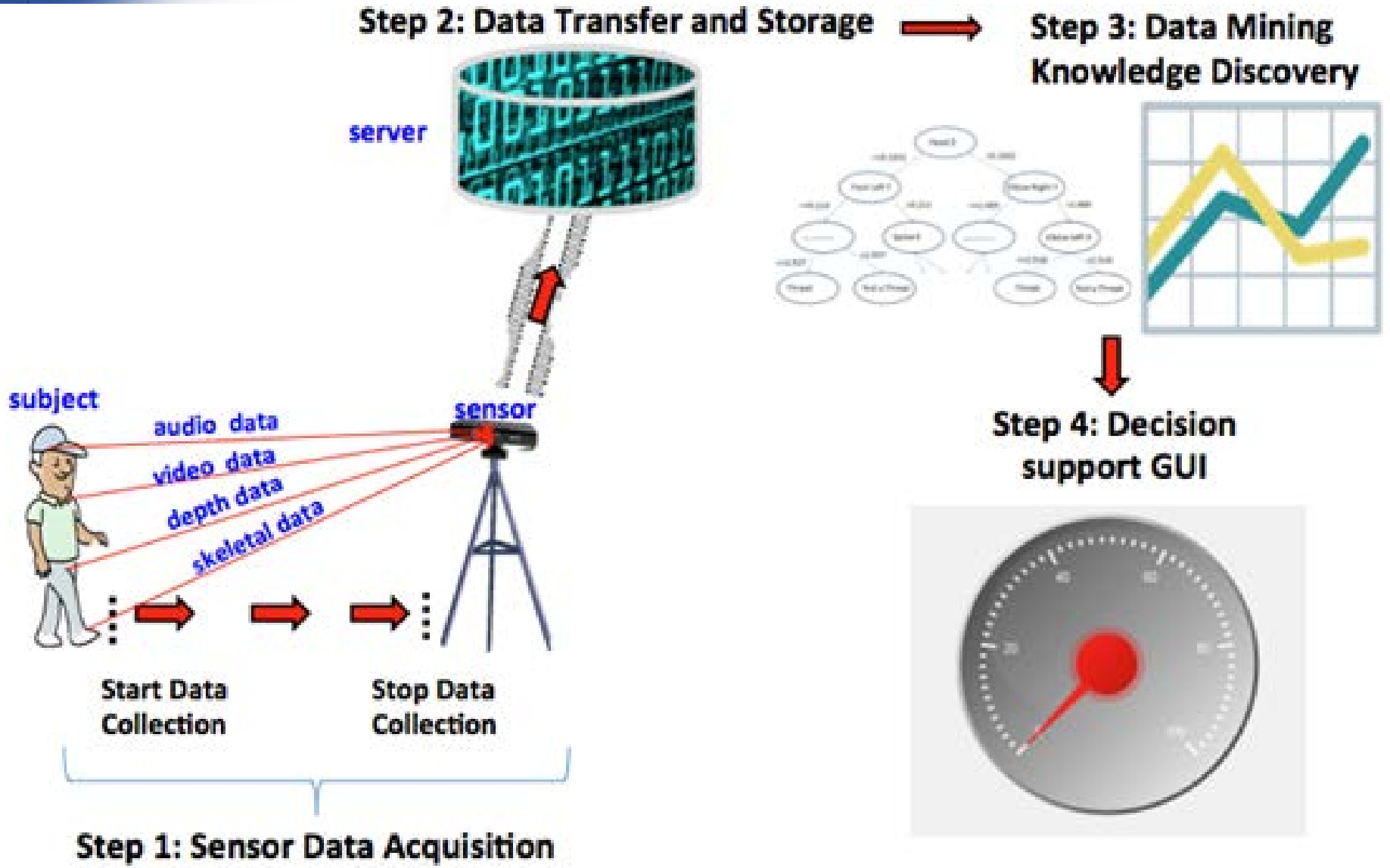
""The most important thing in communication is to hear what isn't being said."

Peter F. Drucker



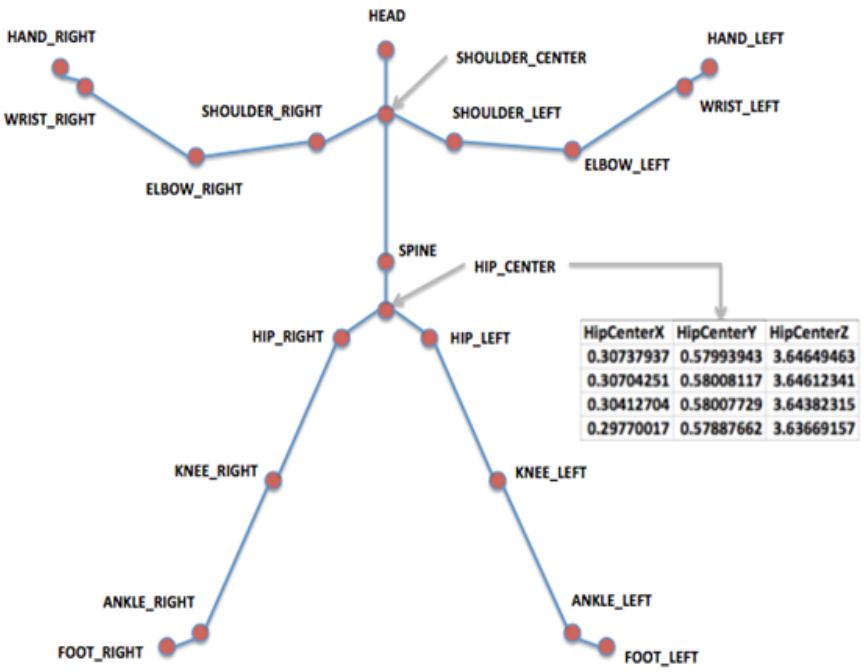
RESEARCH METHODOLOGY

Proposed Methodology



Step 1: Data Acquisition

- Data acquisition hardware setup consists of a sensor system with:
  - **an RGB video camera, and**
  - **an infrared depth sensor**
- Output from sensors is used to create a virtual skeleton of the subject with 20 nodes as shown
- Each nodes collects data pertaining to:
  - **3D Spatial Coordinates (X,Y,Z)**
  - **Timestamp**
  - **Velocities of each node**

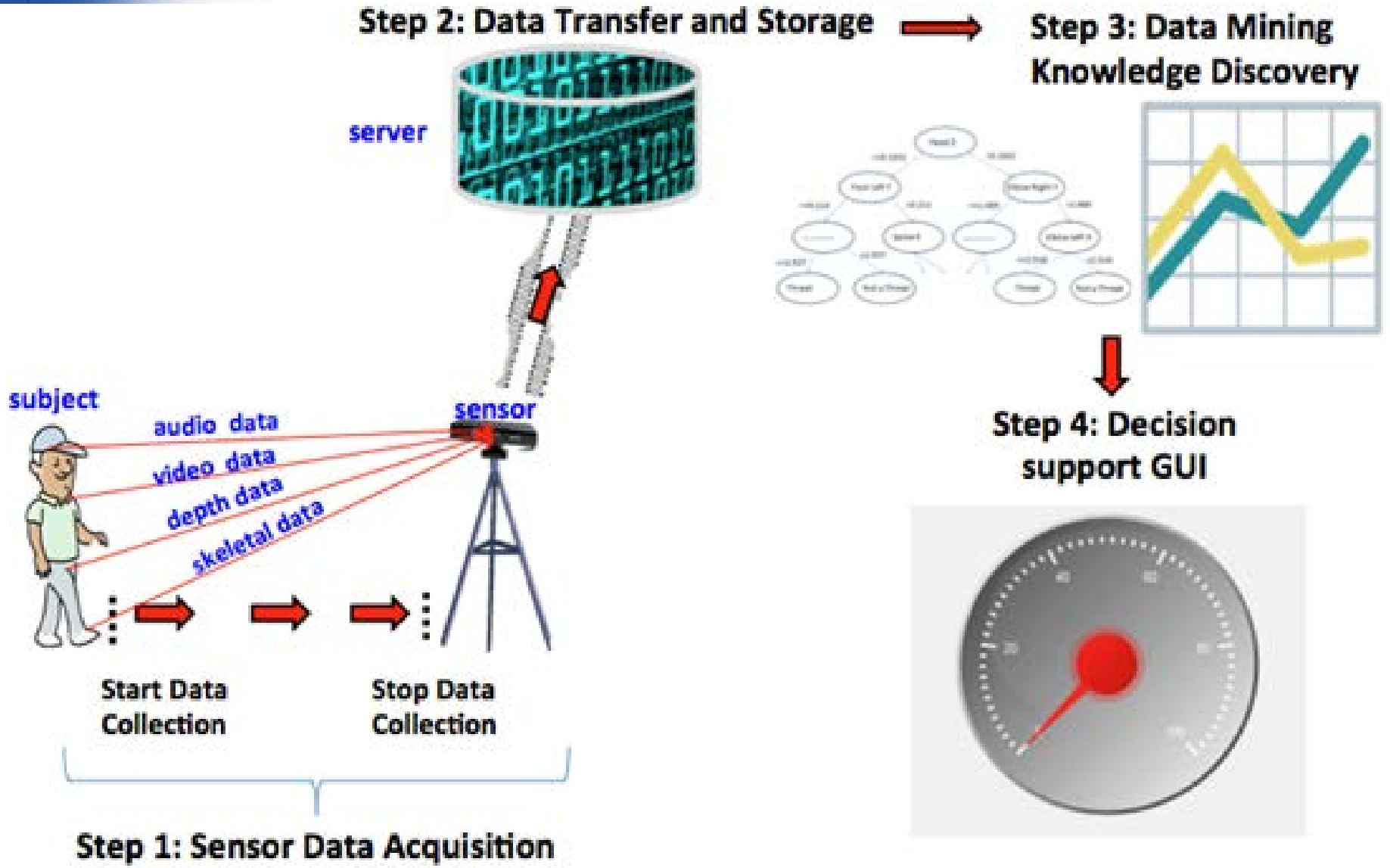


High Fidelity Data, Privacy Preserving

Large Scale Data Base

Head X-Coordinate	Head Y-Coordinate	Head Z-Coordinate	Spine X-Coordinate	Spine Y-Coordinate	Spine Z-Coordinate	Shoulder X-Coordinate	Shoulder Y-Coordinate	Shoulder Z-Coordinate
0.6400	0.7900	0.3500	0.7000	0.2400	0.5000	0.2600	0.1200	0.4300
0.8200	0.3800	0.7200	0.0600	0.4600	0.0700	0.2500	0.7700	0.6900
0.2300	0.9500	0.9200	0.9100	0.9700	0.3800	0.8100	0.6400	0.3000
0.9700	1.0000	0.4700	0.8600	0.7100	0.2400	0.1300	0.4600	0.2600
0.9700	0.2800	0.7100	0.1600	0.0700	0.0900	0.0700	0.5600	0.9200
0.4800	0.9900	0.9800	0.4300	0.6800	0.0400	0.4100	0.4900	0.7700
0.5000	0.7300	0.6700	0.6600	0.1500	0.0900	0.1700	0.6100	0.7600
0.2500	0.8500	0.6000	0.3900	0.9300	1.0000	0.8200	0.5100	0.4100
0.5000	0.6300	0.7900	0.0500	0.8100	0.8000	0.9300	1.0000	0.0500
0.6000	0.5400	0.5800	0.2300	0.2200	0.1200	0.1200	0.8500	0.8200
0.8300	0.7900	0.5400	0.5900	0.3200	0.9900	0.4100	0.5600	0.1400
1.0000	0.6900	0.6300	0.4700	0.6100	0.2400	0.1200	0.5700	0.7800
0.4400	0.0700	0.1100	0.7200	0.9000	0.4600	0.5100	0.8800	0.2600
0.1600	0.4700	0.7400	0.7000	0.5800	0.7100	1.0000	0.9100	0.2400
0.4300	0.6500	0.0000	0.2400	0.0200	0.6500	0.8300	0.8100	0.0000
0.0700	0.5700	0.3300	0.2900	0.3300	0.4000	0.7500	0.6500	0.6100
0.4900	0.9200	0.7100	0.3200	0.6300	0.4400	0.8000	0.9100	0.4200
0.6300	0.1300	0.4600	0.2100	0.2300	0.3100	0.3200	0.5400	0.7700
0.9500	0.1100	0.8100	0.1400	0.2300	0.8800	0.7200	0.1100	0.7200
0.7000	0.4700	0.1100	0.2800	0.0600	0.9700	0.2800	0.1700	0.6700
0.1300	0.4200	0.5300	0.1400	0.7300	0.7100	0.7200	0.3900	0.4400
0.5800	0.8800	0.7600	0.1600	0.6000	0.8300	0.1800	1.0000	0.4400
0.9800	0.9300	0.9900	0.4400	0.0600	0.0800	0.6100	0.9500	0.6100
0.0700	0.7200	0.7200	0.4200	0.8400	0.1700	0.0200	0.7600	0.7700
0.8800	0.6900	0.4400	0.4800	0.8900	0.3700	0.7500	0.8500	0.1700

Proposed Methodology



Step 2: Data Transfer and Storage

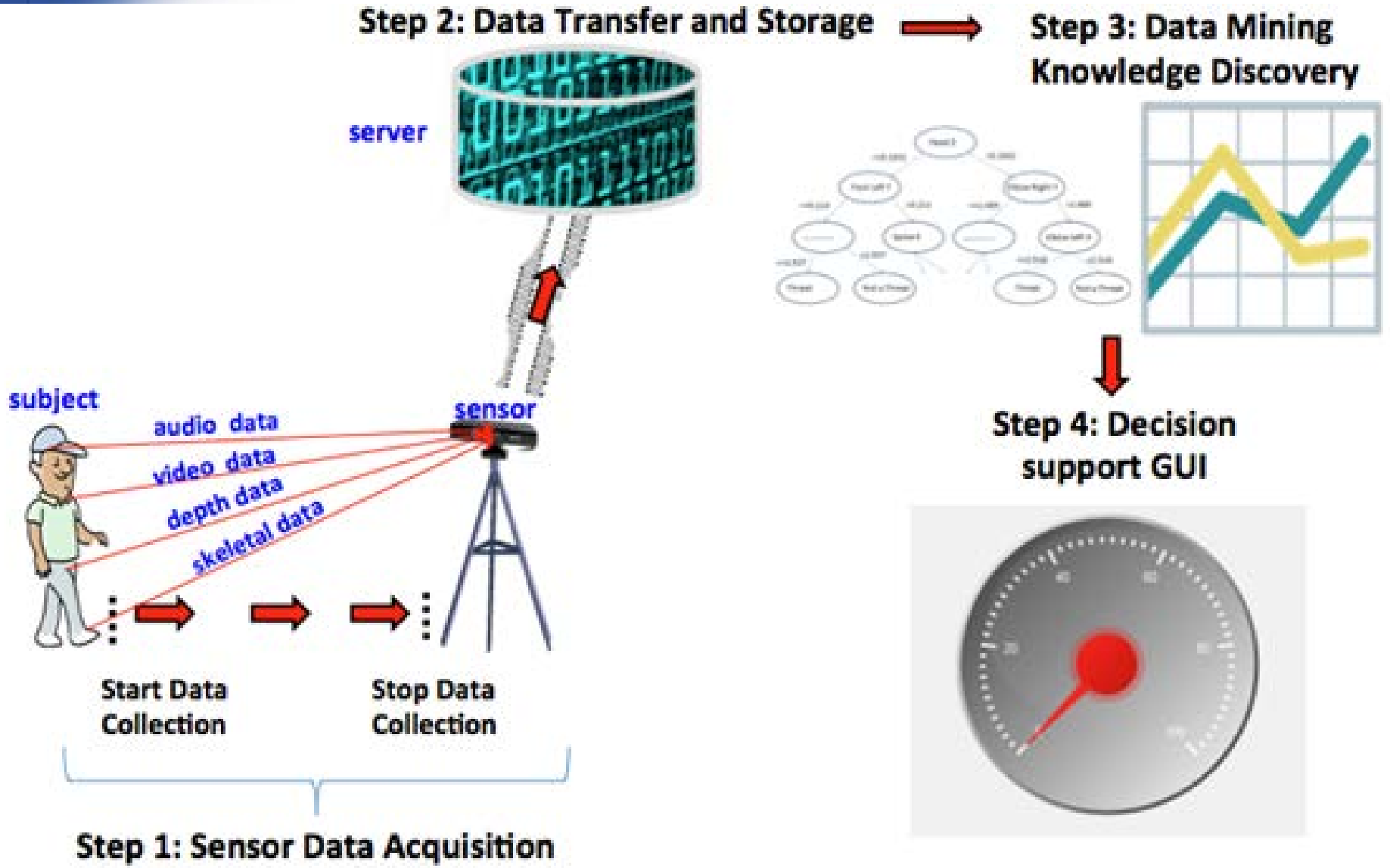
- The data is stored in a structured Relational Database with fields for the following measures:
  - Timestamp
  - Euclidean Coordinates
  - Velocities of each node
  - Boolean "Threat Class" defining whether the data collected during training was for a threat action or not.

Step 2: Data Transfer and Storage

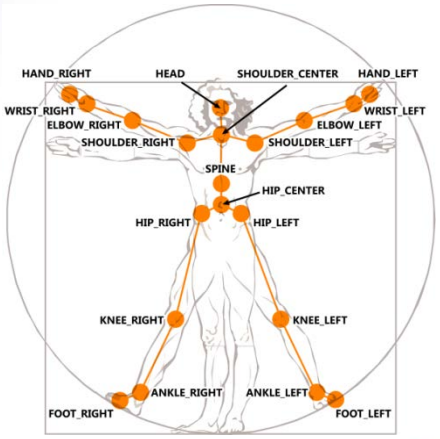
- The data is stored in a structured Relational Database with fields for the following measures:

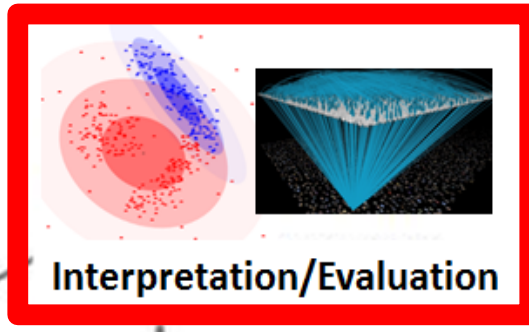
Timestamp	Node X Coordinate	Node Y Coord.	Node Z Coord.	Velocity of Node X Coord.	.....	Threat Class
1346879	3.04356	2.98750	1.25673	0.25677		FALSE
1346902	3.25831	5.63178	4.77721	6.78103		TRUE
⋮						

Proposed Methodology



Step3: Data Mining/Knowledge Discovery





$$info(A) = -\sum_{i=1}^{m} f_i \log_2 f_i$$

$$argmax\, P(C = c)_m = \prod_{i=1} p(Ai = ai|C)$$

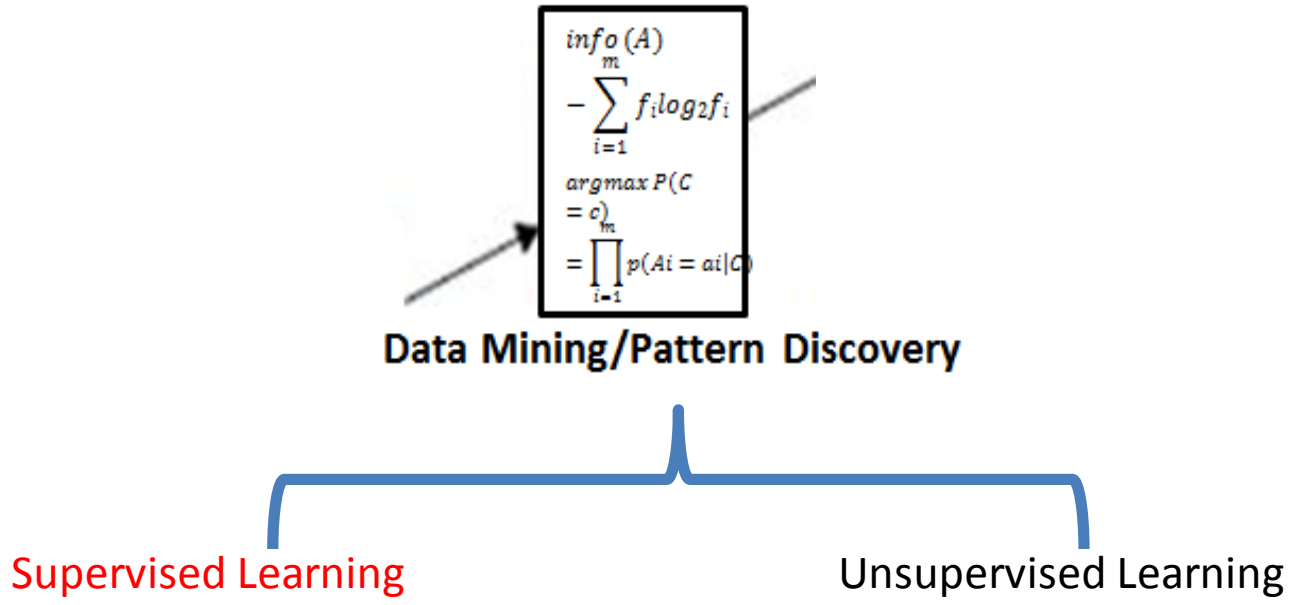
Data Mining/Pattern Discovery

Data Transformation

Data Selection and Cleaning

Data

Knowledge Discovery in Data Bases



Supervised VS Unsupervised Learning

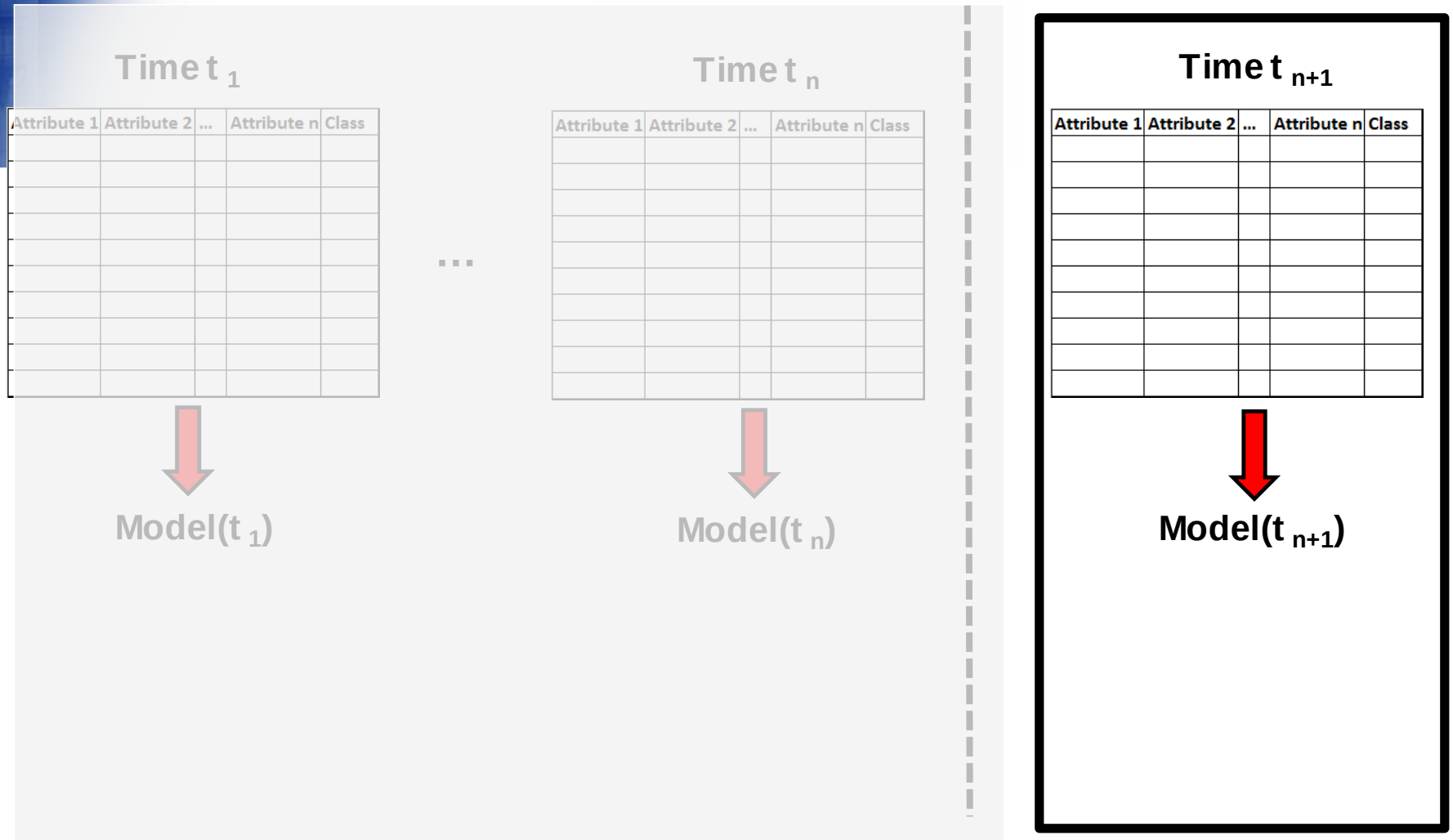
Supervised

- y=F(x): true function
- D: labeled training set
- D: $\{x_i, F(x_i)\}$
- Learn:
  G(x): model trained to predict labels D
- Goal:
  $E[(F(x)-G(x))^2] \approx 0$
- Well defined criteria:
  Accuracy, RMSE, ...

Unsupervised

- Generator: true model
- D: unlabeled data sample
- D: $\{x_i\}$
- Learn
  Underlying data structure
- Goal:
  Find natural patterns
- Well defined criteria:
  varies

Capturing Threat Emergence



Data Mining Decision Tree Induction

Given a time stamped Data Set (t),

Feature 1	Feature 2	...	Feature N	Class
$A_{1,1}$	$A_{2,1}$		$A_{N,1}$	$C_{j,1}$
.	.		.	.
.	.		.	.
.	.		.	.
$A_{1,M}$	$A_{2,M}$		$A_{N,M}$	$C_{j,M}$

$$Entropy(T) = -\sum_{j} p(C_j \mid T) \log_2 p(C_j \mid T)$$

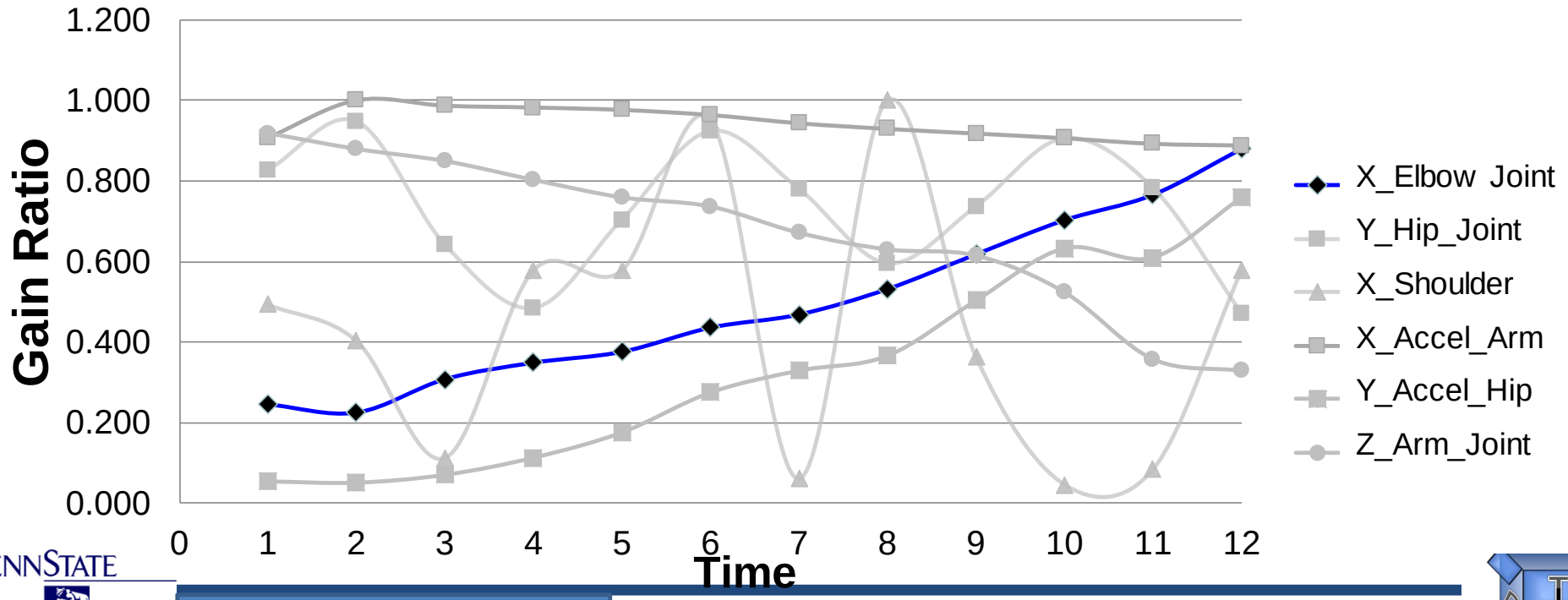
$$GAIN(X) = Entropy(T) - \left(\sum_{i=1}^{k} \frac{T_i}{T} Entropy_X(T_i) \right)$$

$$\text{Gain ratio(X)} = \frac{Gain(X)}{-\sum_{i=1}^{k} \frac{|T_i|}{|T|} \cdot \log_2 \frac{|T_i|}{|T|}}$$

Tucker C., H.M. Kim,"Trend Mining for Predictive Product Design", Transactions of ASME: Journal of Mechanical Design, Vol. 133, No. 11, 2011.

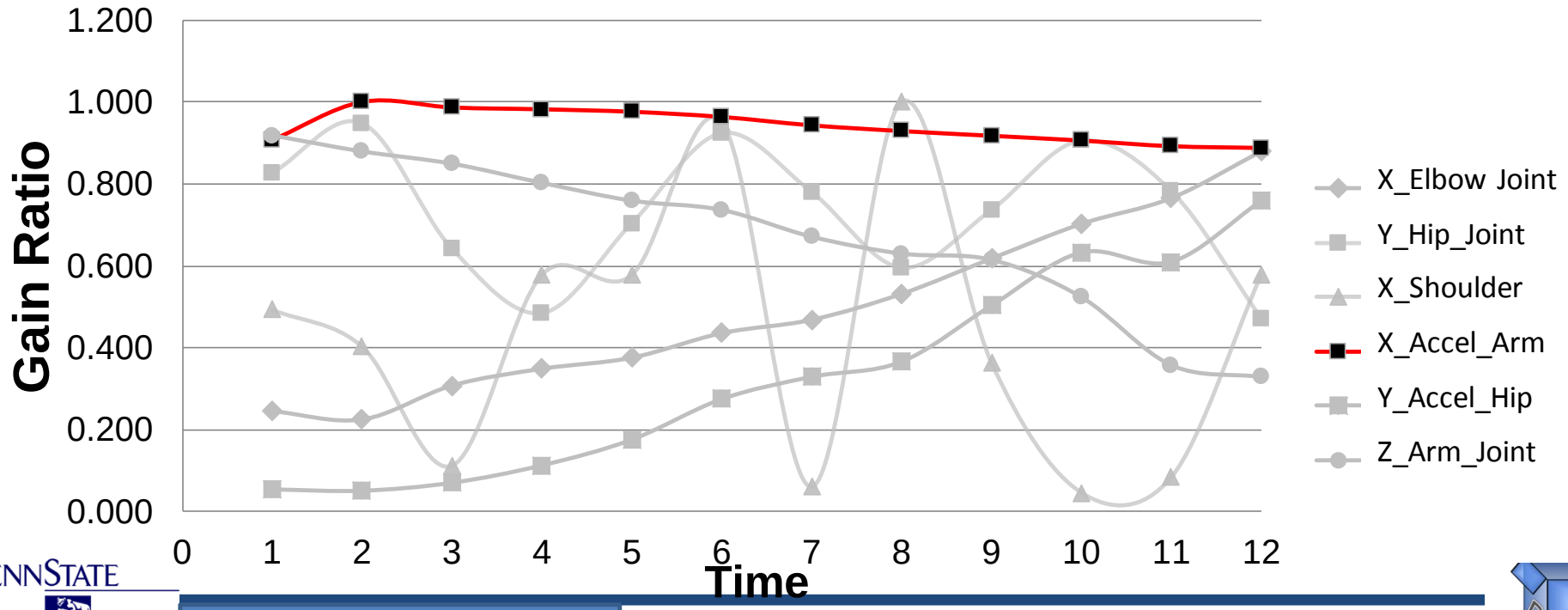
Features	Time Series Gain Ratio												Predict
	t1	t2	t3	t4	t5	t6	t7	t8	t9	t10	t11	t12	t13_predict
X_Elbow Joint	0.245	0.225	0.308	0.349	0.376	0.436	0.468	0.532	0.618	0.702	0.765	0.879	0.919
Y_Hip_Joint	0.827	0.948	0.642	0.485	0.704	0.924	0.780	0.596	0.737	0.906	0.782	0.472	0.789
X_Shoulder	0.493	0.403	0.112	0.578	0.578	0.951	0.061	1.000	0.363	0.046	0.084	0.578	0.541
X_Accel_Arm	0.907	1.000	0.987	0.982	0.976	0.963	0.943	0.929	0.917	0.906	0.892	0.888	0.877
Y_Accel_Hip	0.054	0.051	0.070	0.113	0.176	0.275	0.329	0.366	0.503	0.633	0.610	0.759	0.842
Z_Arm_Joint	0.918	0.879	0.849	0.803	0.759	0.737	0.671	0.630	0.615	0.524	0.358	0.329	0.270

Feature Gain Ratio Plot Over Time

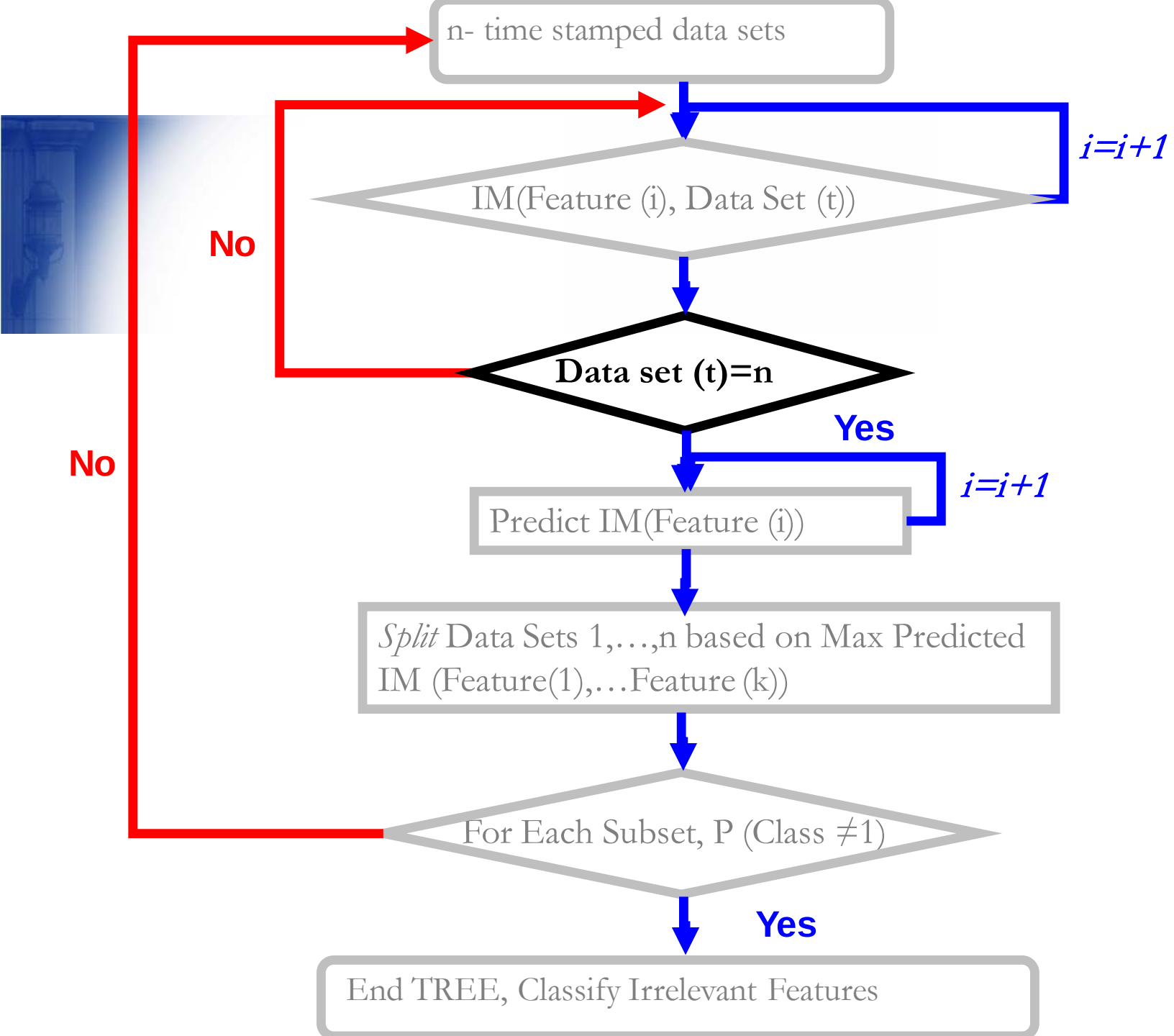


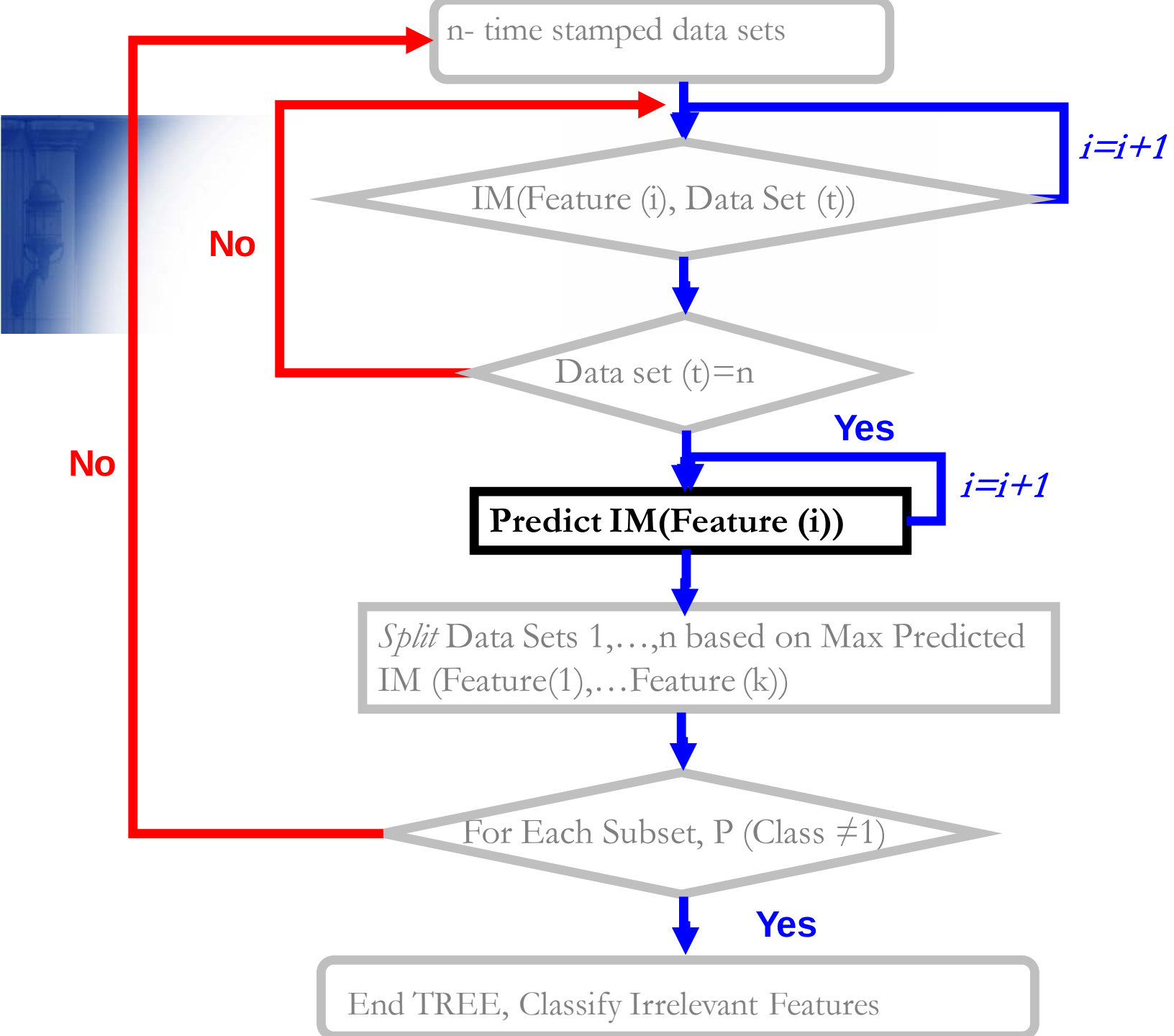
Features	Time Series Gain Ratio												Predict
	t1	t2	t3	t4	t5	t6	t7	t8	t9	t10	t11	t12	t13_predict
X_Elbow Joint	0.245	0.225	0.308	0.349	0.376	0.436	0.468	0.532	0.618	0.702	0.765	0.879	0.919
Y_Hip_Joint	0.827	0.948	0.642	0.485	0.704	0.924	0.780	0.596	0.737	0.906	0.782	0.472	0.789
X_Shoulder	0.493	0.403	0.112	0.578	0.578	0.951	0.061	1.000	0.363	0.046	0.084	0.578	0.541
X_Accel_Arm	0.907	1.000	0.987	0.982	0.976	0.963	0.943	0.929	0.917	0.906	0.892	0.888	0.877
Y_Accel_Hip	0.054	0.051	0.070	0.113	0.176	0.275	0.329	0.366	0.503	0.633	0.610	0.759	0.842
Z_Arm_Joint	0.918	0.879	0.849	0.803	0.759	0.737	0.671	0.630	0.615	0.524	0.358	0.329	0.270

Feature Gain Ratio Plot Over Time



22


n- time stamped data sets
IM(Feature (i), Data Set (t))
i=i+1
No
Data set (t)=n
Yes
No
i=i+1
Predict IM(Feature (i))
Split Data Sets 1,…,n based on Max Predicted IM (Feature(1),…Feature (k))
For Each Subset, P (Class ≠1)
Yes
End TREE, Classify Irrelevant Features


n- time stamped data sets
IM(Feature (i), Data Set (t))
i=i+1
No
Data set (t)=n
Yes
No
i=i+1
Predict IM(Feature (i))
Split Data Sets 1,…,n based on Max Predicted IM (Feature(1),…Feature (k))
For Each Subset, P (Class ≠1)
Yes
End TREE, Classify Irrelevant Features

Holt-Winters Forecasting

The (k) step-ahead forecasting model is defined as:

$$\hat{y}_t(k) = L_t + kT_t + I_{t-s+k}$$

Where:

Level Lt (the level component):

$$L_t = \alpha(y_t - I_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1})$$

Trend Tt (the slope component):

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$

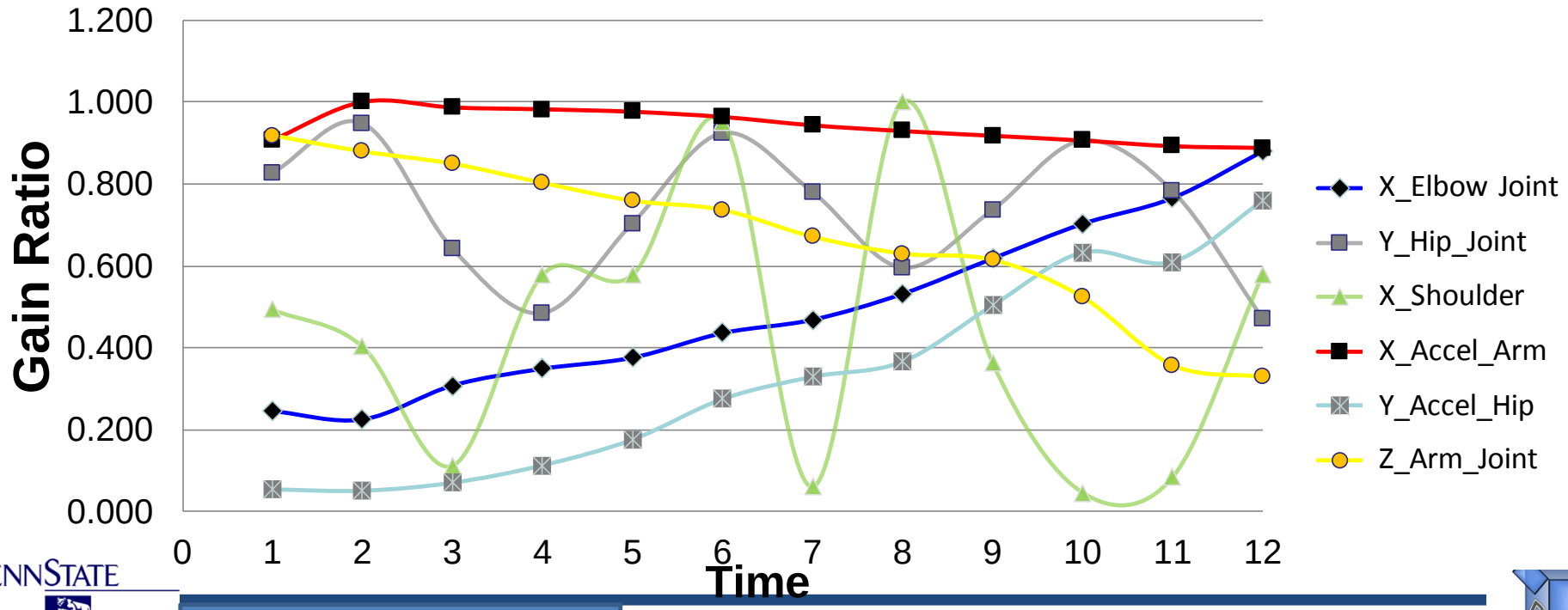
Season It (the seasonal component):

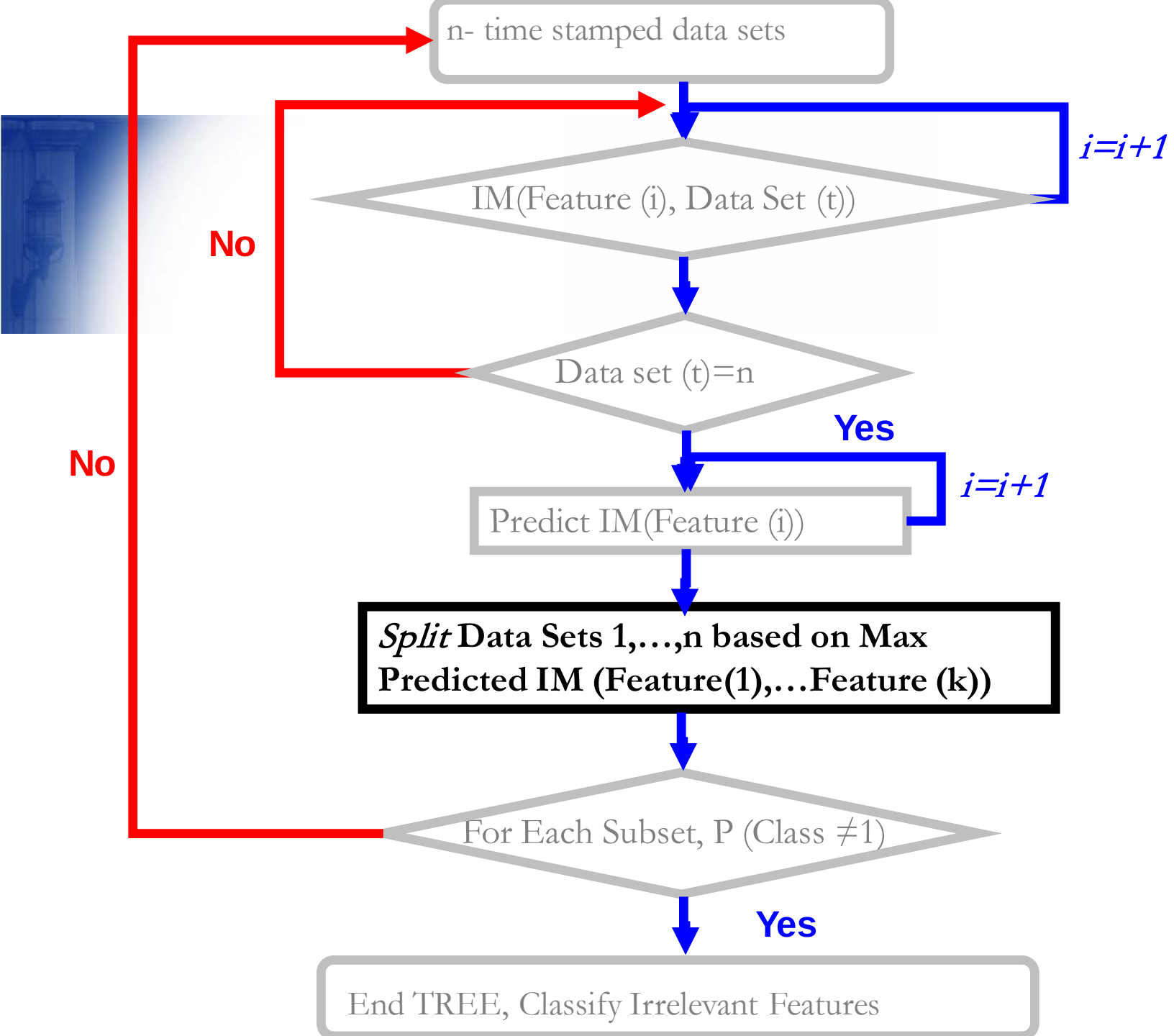
$$I_t = \delta(y_t - L_t) + (1-\delta)I_{t-s}$$

The smoothing parameters $\alpha,\gamma\ \delta$, are in the range $\{0,1\}$

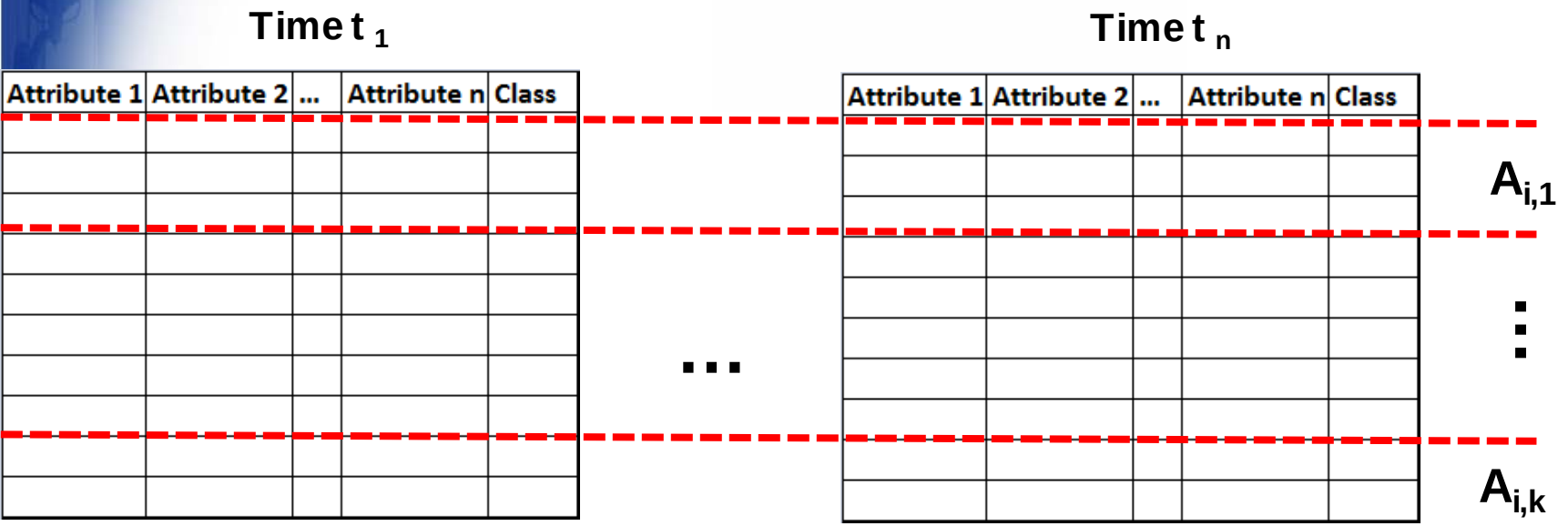
Features	Time Series Gain Ratio												Predict
	t1	t2	t3	t4	t5	t6	t7	t8	t9	t10	t11	t12	t13_predict
X_Elbow Joint	0.245	0.225	0.308	0.349	0.376	0.436	0.468	0.532	0.618	0.702	0.765	0.879	0.919
Y_Hip_Joint	0.827	0.948	0.642	0.485	0.704	0.924	0.780	0.596	0.737	0.906	0.782	0.472	0.789
X_Shoulder	0.493	0.403	0.112	0.578	0.578	0.951	0.061	1.000	0.363	0.046	0.084	0.578	0.541
X_Accel_Arm	0.907	1.000	0.987	0.982	0.976	0.963	0.943	0.929	0.917	0.906	0.892	0.888	0.877
Y_Accel_Hip	0.054	0.051	0.070	0.113	0.176	0.275	0.329	0.366	0.503	0.633	0.610	0.759	0.842
Z_Arm_Joint	0.918	0.879	0.849	0.803	0.759	0.737	0.671	0.630	0.615	0.524	0.358	0.329	0.270

Feature Gain Ratio Plot Over Time

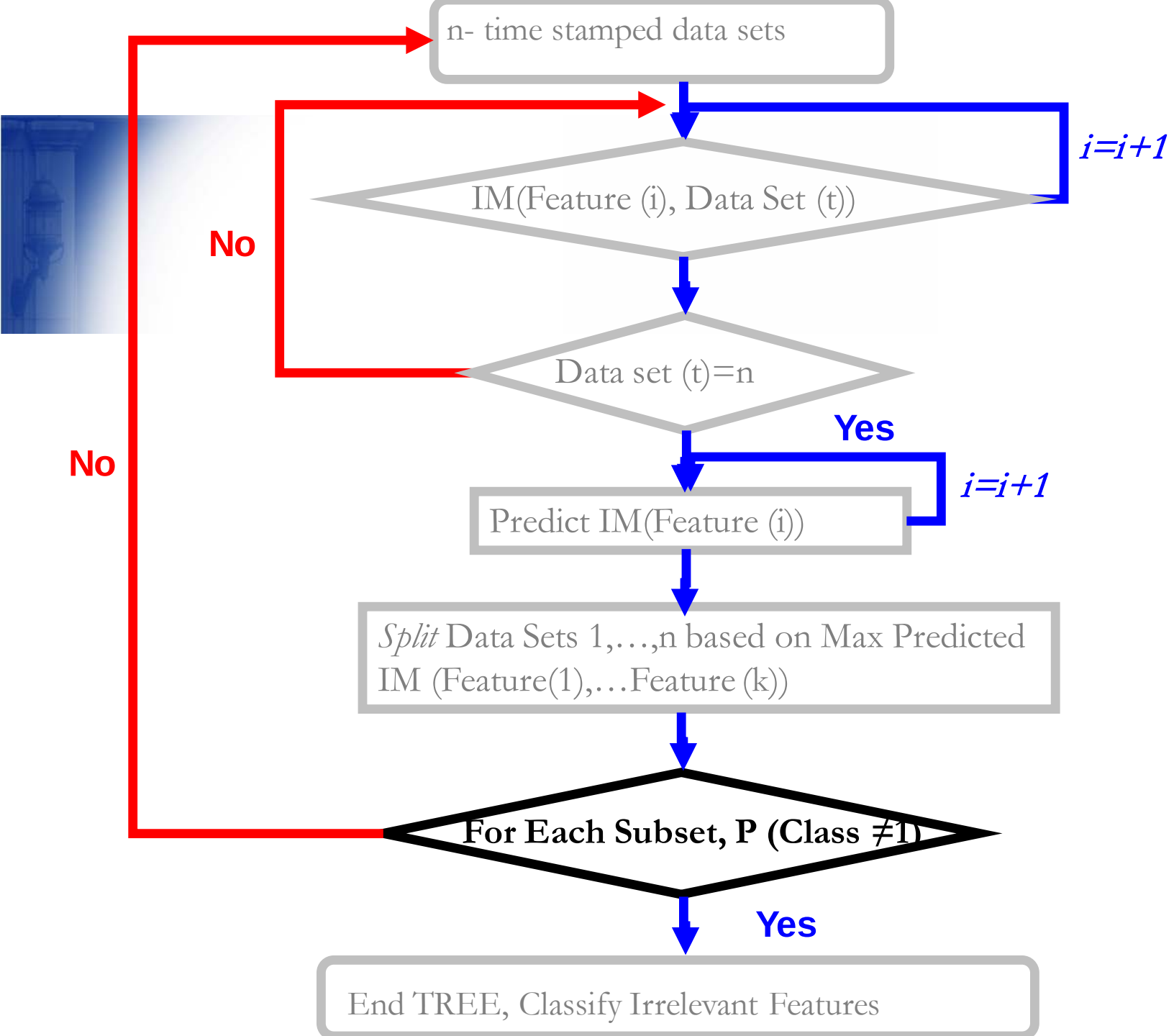


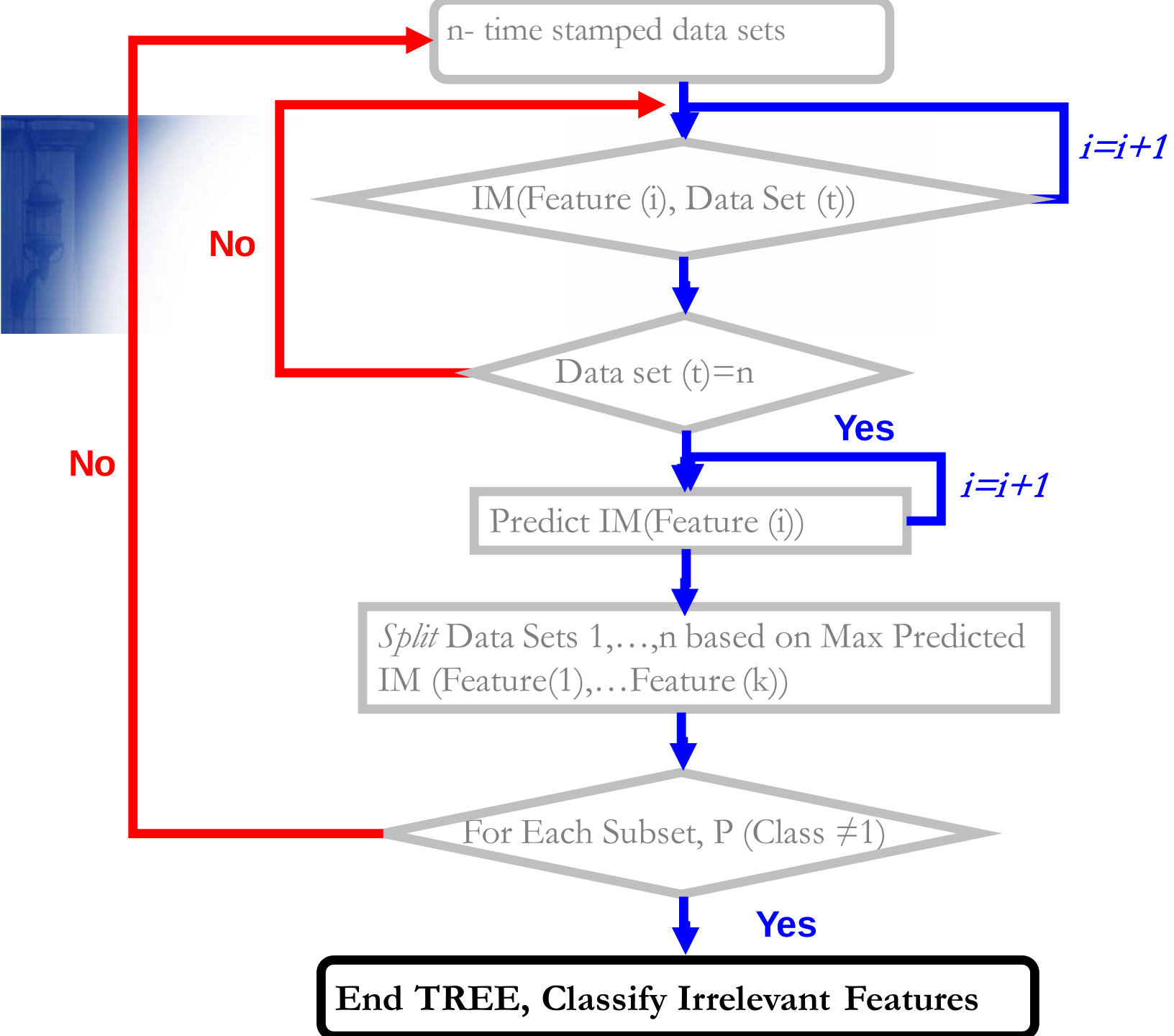

n- time stamped data sets
IM(Feature (i), Data Set (t))
i=i+1
No
Data set (t)=n
Yes
No
i=i+1
Predict IM(Feature (i))
Split Data Sets 1,…,n based on Max Predicted IM (Feature(1),…Feature (k))
For Each Subset, P (Class ≠1)
Yes
End TREE, Classify Irrelevant Features

Split Data Sets ($t_1,\ldots,t_n$) : Max IM



Split Data Sets (1,..,n) based on **k** mutually exclusive Feature values of Feature $\mathbf{A_i}$


n- time stamped data sets
IM(Feature (i), Data Set (t))
i=i+1
No
Data set (t)=n
Yes
No
i=i+1
Predict IM(Feature (i))
Split Data Sets 1,…,n based on Max Predicted IM (Feature(1),…Feature (k))
For Each Subset, P (Class ≠1)
Yes
End TREE, Classify Irrelevant Features


n- time stamped data sets
IM(Feature (i), Data Set (t))
i=i+1
No
Data set (t)=n
Yes
No
i=i+1
Predict IM(Feature (i))
Split Data Sets 1,…,n based on Max Predicted IM (Feature(1),…Feature (k))
For Each Subset, P (Class ≠1)
Yes
End TREE, Classify Irrelevant Features

Data Mining Predictive Model

Time t_1

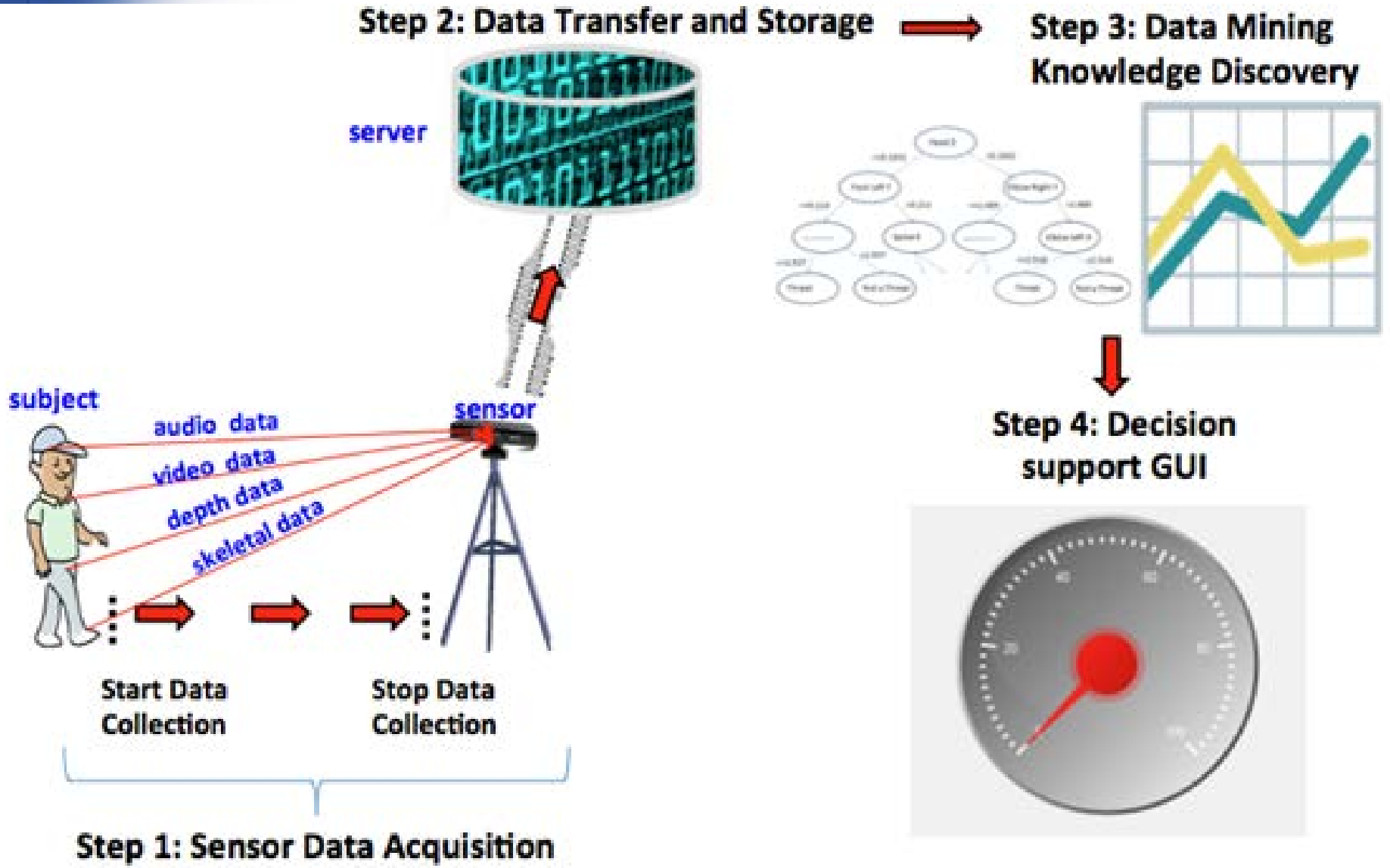
Attribute 1	Attribute 2	...	Attribute n	Class

...

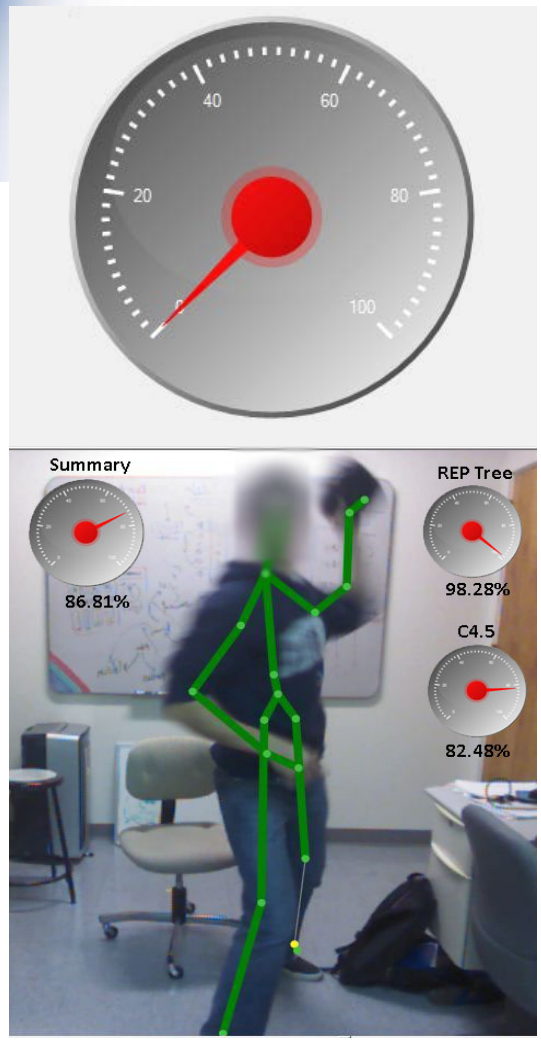
Time t_n

Attribute 1	Attribute 2	...	Attribute n	Class

Proposed Methodology



Step 4: Decision Support



- Early Warning System (EWS) is a graphical user interface (GUI) that display the "percentage probability of threat/violent action being committed".

APPLICATION CASE STUDY

Possible Threat Scenario

BBC UK (2008)

CASE STUDY: TEST DATA

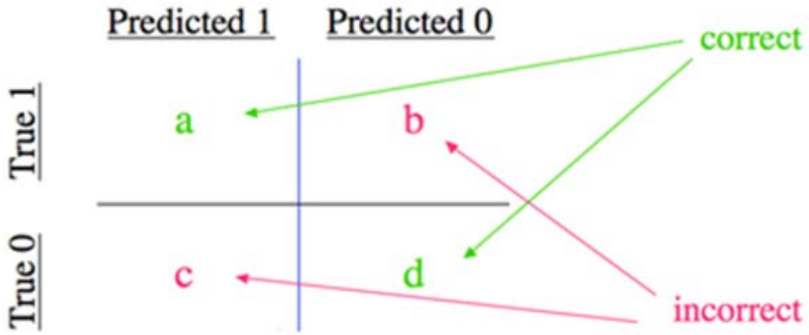
- Voluntary participants from the University community were invited to enact the threat and non-threat actions
- Recreated in an indoor space, similar to a high profile speech
- The data collected is then used to train the predictive models
- The study was approved by the IRB and the ORP at the Pennsylvania State University, University Park campus, under the title "A Dynamic Pattern Recognition Framework for Mining and Predicting Emerging Threats" and is filed as IRB # 40258.
- **Study: 24 Subjects spanning 2 months**

THREAT PREDICTION RESULTS

Low level threat prediction

High level threat prediction

RESULTS



Accuracy=(a+d)/(a+b+c+d)
Precision=a/(a+c)
Recall=a/(a+b)

Accuracy of Ensemble Methods: 86.8%

CONCLUSION AND FUTURE WORK

Conclusion and Future Work

- The most common surveillance systems today are reactive in nature and are not capable of actively predicting the emergence of a threat by analyzing past data collected.
- Privacy preserving data mining methodology
- This methodology takes the first step towards addressing these issues while providing promising results
- Expand the definition of "threat"

ACKNOWLEDGEMENTS AND REFERENCES

Contributors:

- Dr. Conrad S. Tucker, D.A.T.A. Lab members, Research Participants from PSU.

References:

1. Quinlan, J. R. C4.5: Programs for Machine Learning. Morgan Kaufmann Publishers, 1993.
2. Joshi, Karuna Pande. "Analysis of data mining algorithms." *University of Minnesota. Retrieved July* 25 (1997): 2005.
3. J. Han, M. Kamber, J. Pei, Data Mining: Concepts and Techniques, Third edition, 2011.
4. Data-Driven Decision Tree Classification for Product Portfolio Design Optimization, Conrad S. Tucker and Harrison M. Kim, J. Comput. Inf. Sci. Eng. 9, 041004 (2009), DOI:10.1115/1.3243634.
5. J. L. Raheja, A. Chaudhary, K. Singal, Tracking of fingertips and centers of palm using KINECT, International Conference on Computational Intelligence, Modeling & Simulation, 2011, 248-252.
6. Ya-Li Hou and Grantham K.H. Pang, Human detection in crowded scenes, IEEE international conference on image processing, 2010, 721-724.