



Multiple Kernel Learning for Heterogeneous Anomaly Detection: Algorithm and Aviation Safety Case Study

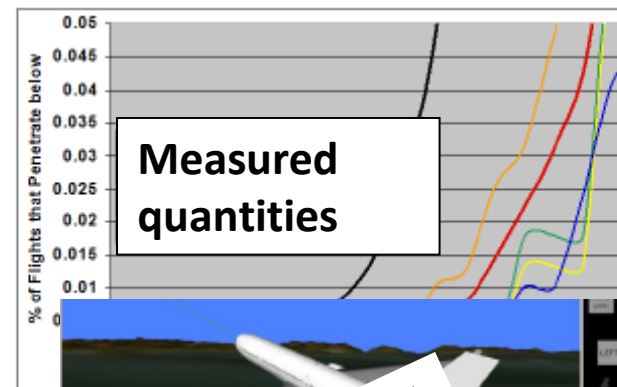
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Motivation

Flight Data Monitoring

Automatic identification and causal analysis of hazards from data streams with mixed attributes



PERSON	
Function.Flight Crew	
652 - Captain	
5131 - Check Pilot	
653 - First Officer	
655 - Flight Engineer/Second	
5132 - Instructor	
606 - Pilot Flying	
607 - Pilot Not Flying	
654 - Relief Pilot	
651 - Single Pilot	
5133 - Trainee	
5134 - Other / Unknown	
Qualification.Flight Crew	
700 - Student	
5150 - Sport/Recreational	
701 - Private	
704 - Commercial	
705 - Air Transport Pilot	
707 - Flight Instrn	
703 - Multiengine	
702 - Instrument	
706 - Flight Engineer	
5148 - Rotorcraft	
5147 - Lighter-Than-Air	
5149 - Sea	
5146 - Glider	
Experience.Flight Crew	
746 - Total	
748 - Last 90 Days	
747 - Type	

Text report

5124 - Instructor	
5125 - Trainee	
Local	
Oceanic	
Supervisor/CIC	
Traffic Management	
128 - Other / Unknown	
Qualification.Air Traffic Control	
5145 - Fully Certified	
712 - Developmental	
Experience.Air Traffic Control	
730 - Radar (Yrs)	
732 - Non Radar (Yrs)	
733 - Military (Yrs)	
734 - Supervisory (Yrs)	
735 - Time Certified	
in Pos 1 (mon)	
735 - Time Certified	
in Pos 1 (yrs)	



Fleet wide analysis

Flight Data Monitoring

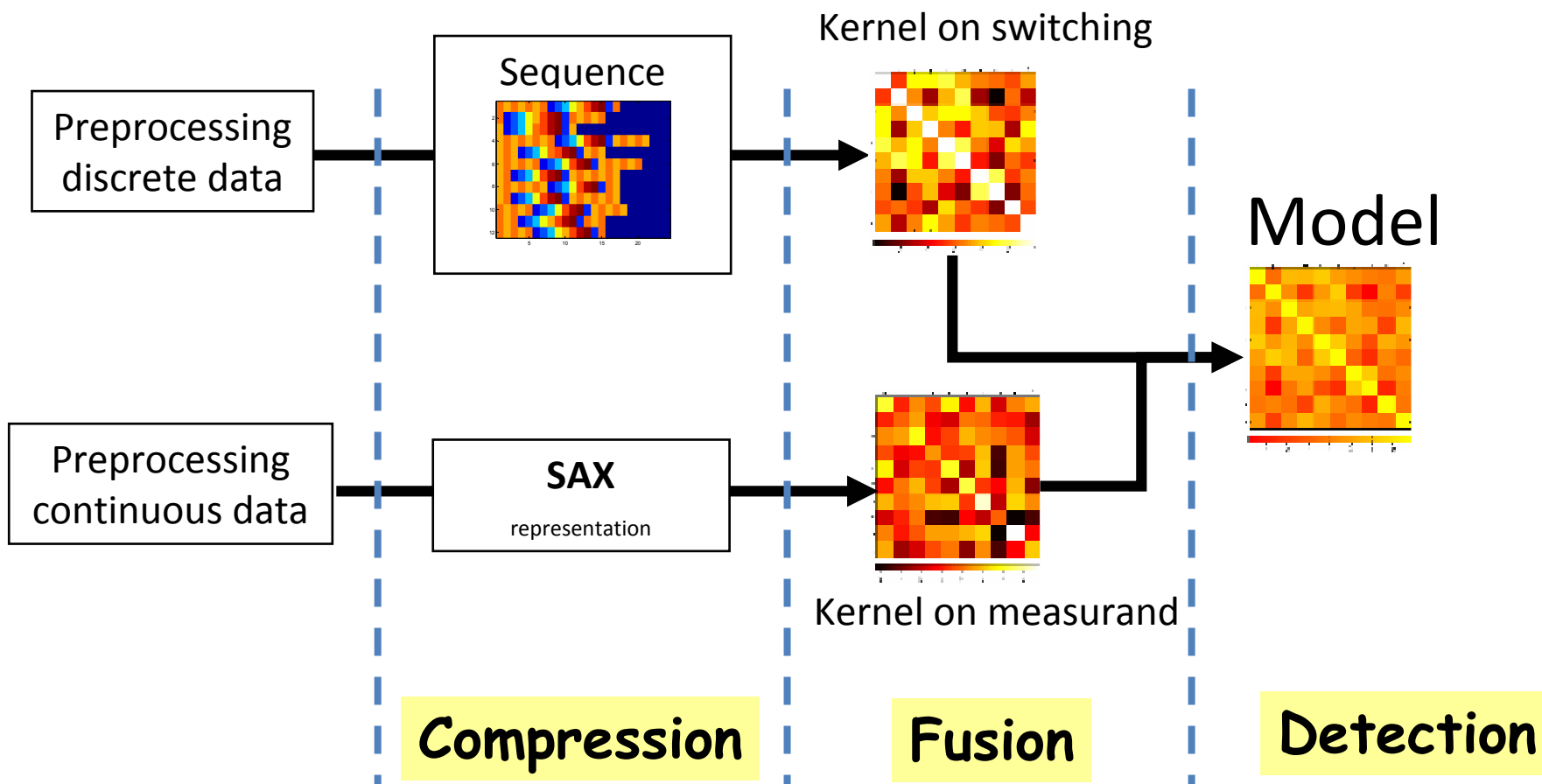
Sequences D and continuous data streams C interactions

How to integrate all information in a concise and intuitive manner?

Compression,
Feature extraction,
Fusion,
Anomaly detection



Mining Framework



We come to the SAX (Symbolic Aggregate Approximation) Homepage!

SAX was invented by Eamonn Keogh and Jessica Lin, 2002



**Multivariate symbolic sequences.
Multivariate continuous sequences.**



Pair wise Similarity Measure

$$\begin{array}{l} \text{Flight } i \longrightarrow \\ \text{Flight } j \longrightarrow \end{array} K_{\diamond}(f_i, f_j) = \frac{L(h(s_i, s_j))}{\sqrt{L(s_i) \times L(s_j)}}$$

Detector
One Class nu-SVMs

Normalized Longest
Common Subsequence

For more information, please see

B. Schölkopf, A. Smola, R. Williamson,
and P. L. Bartlett. New support vector
algorithms. *Neural Computation*, 12,
2000, 1207-1245.

- Solves a convex and quadratic optimization problem.
- **Can appropriately introduce a mixture of kernels in the convex cost function.**
- Enables using non-linear kernel functions to learn complex separating planes.
- Results a model that can be used to classify new examples.



Optimization problem

One class SVMs training algorithms require solving the quadratic problem

Dual form

$$Q_{\min} = \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j \left(\sum_{\lambda} \beta_{\lambda} K_{i,j}^{\lambda} \right)$$

Subject to:

$$\sum_i \alpha_i = 1$$

Linear equality
constraint

$$\nu \in [0,1],$$

Control parameter

$$0 \leq \alpha_i \leq \frac{1}{l\nu}, \forall i$$

Bounds on design
variables

α : Lagrange multipliers of the primal QP problem



Anomaly scores

Decision boundary is determined only by margin and non-margin support vectors obtained by solving the QP problem

$$h(\alpha, \beta, f_z, \rho) = \sum_i \alpha_i \left(\sum_{\lambda} \beta_{\lambda} K_{i,z}^{\lambda} \right) - \rho$$

Datapoints with $\alpha_k > 0$ will be the support vectors

Indicator

*Sign of h : if negative - outlier
if positive - normal*

Value of h : degree of anomalousness



Experiment

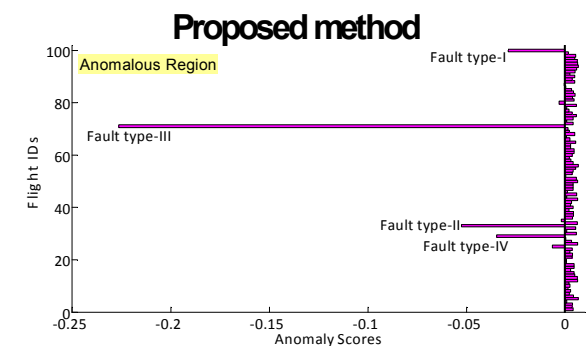
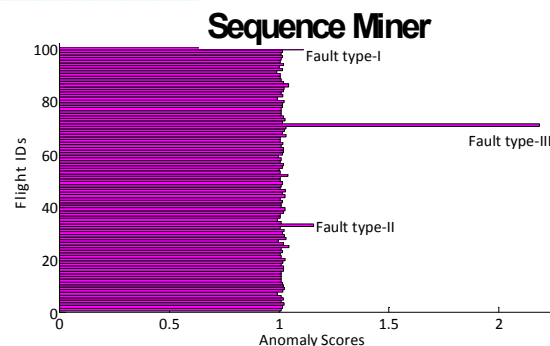
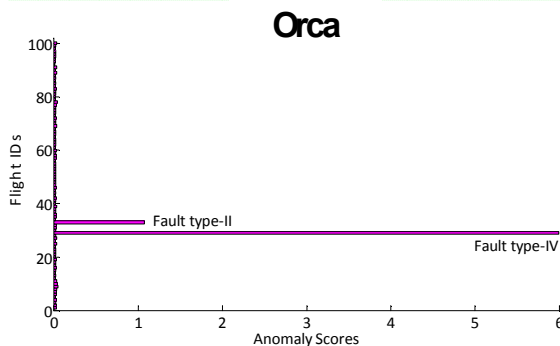
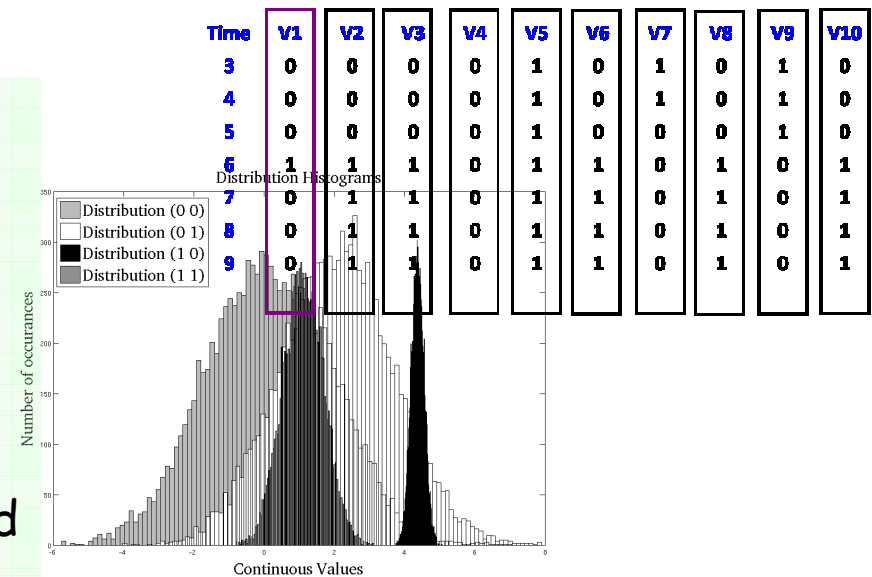
Simulation data

Type 1 - (Missing event) Flaps were not extended to normal full deployment at landing.

Type 2 - (Extra event) Landing gear was retracted after being deployed on final approach.

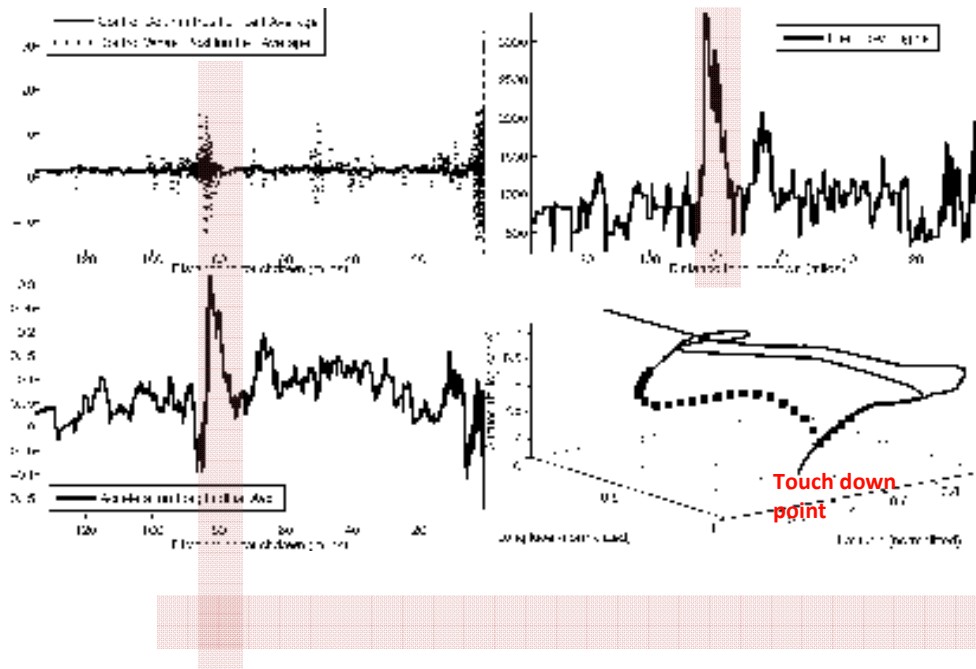
Type 3 - (Out of order event) Gear deployed before initial flaps below flaps limit.

Type 4 - (Continuous anomaly) High bank angles or rate of descent below 1,000 ft.





Case study: FOQA anomaly detection



Normal Extra Missing

Flaps1 On
Landing_Gear_Sel_Dwn On
Flaps2 On
FlapsFull On
Ground_Spoilers_Deployed On
Landing_Gear_Sel_Dwn Off
FlapsFull Off
Flaps2 Off
Flaps1 Off
Flaps1 On
Landing_Gear_Sel_Dwn On
Flaps2 On
FlapsFull On

- The traditional methods cannot detect and monitor these anomalous activities that may have occurred simultaneously and are heterogeneous in nature.



Conclusion

What can we summarize ?

Performs

... anomaly detection on multivariate mixed attributes where sequences may influence the system dynamics which is reflected on the continuous data streams.

Application

1. Support flights safety experts
2. Schedule maintenance

Highlights

- .. High detection rate on most operationally significant anomalies in fleet wide analysis on large datasets
- .. Discover some "unknown unknowns"



Thank you

- Contact and feedback:
 - Santanu Das
 - Santanu.Das-1@nasa.gov
- More resources on Dashlink website:
<https://c3.ndc.nasa.gov/dl/topic/multiple-kernel-learning-based-heterogeneous-algorithm-2/>
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