

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

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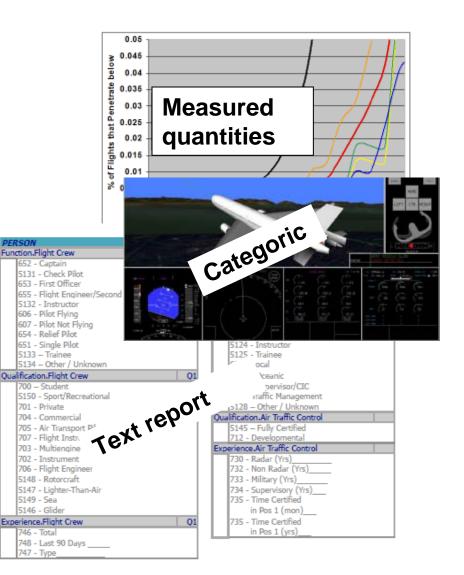
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Motivation



Flight Data Monitoring

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





Fleet wide analysis

Flight Data Monitoring

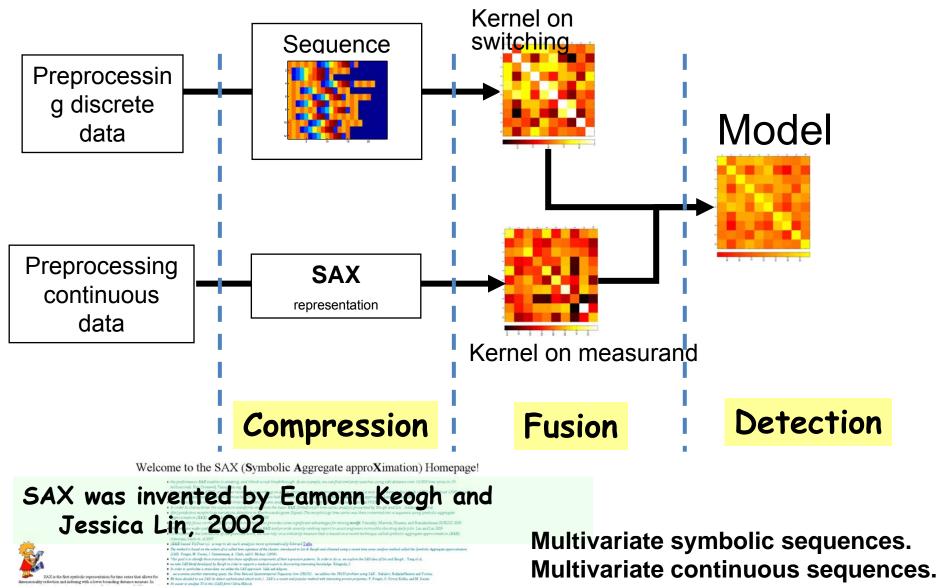
Sequences D and continuous data streams C interactions

How to integrate all information in a <u>concise</u> and <u>intuitive</u> manner?

Compression, Feature extraction, Fusion, Anomaly detection



Mining Framework





Pair wise Similarity Measure

Flight
$$\xrightarrow{i}$$

Flight \xrightarrow{j}
 $K_{\Diamond}(f_i, f_j) = \frac{L(h(s_i, s_j))}{\sqrt{L(s_i) \times L(s_j)}}$

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.

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

Subject to:

Control parameter

 α : Lagrange multipliers of the primal QP problem

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

 $\sum_{i} \alpha_{i} = 1$

 $v \in [0,1],$



Anomaly scores

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

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

Data points with $\alpha_k > 0$ will be the support vectors

Indicator

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

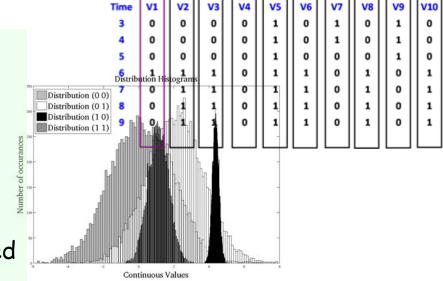
Value of h: degree of anomalousness



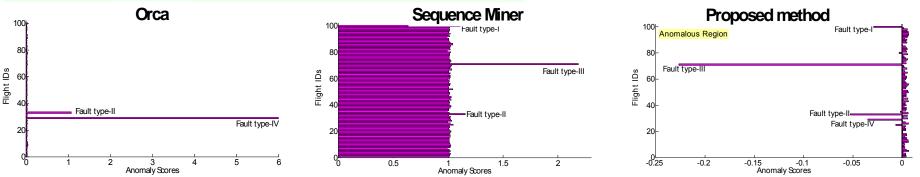
Experiment

Simulation data

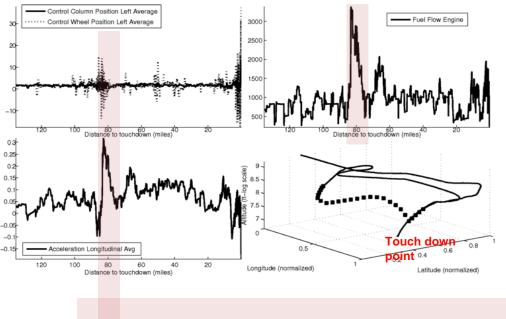
- Type 1 (Missing event) Flaps were not extended to normal full deployment at landing.
- Type 2 (Extra event) Landing gear was retracted after being deployed on final approach.
- Type 3 (Out of order event) Gear deployed before initial flaps below flaps limit.



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



Case study: FOQA anomaly detection



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

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

Natsyn

Conclusion

What can we summarize ?

Performs

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

Application

- 1. Support flights safety experts
- 2. Schedule maintenance

<u>Highlights</u>

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



Thank you

- Poster ID: 59
- Contact and feedback:
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• More resources on Dashlink website:

https://c3.ndc.nasa.gov/dl/topic/multiple-kernel-learning-basedheterogeneous-algorithm-2/

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