Using ADOPT Algorithm and Operational Data to Discover Precursors to Aviation Adverse Events

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Outline

• **Background**
  – Precursor discovery problem, uses, challenges

• **Methodology**
  – ADOPT algorithm

• **Case Studies**
  – Take-off Stall Hazard
  – STAR procedure adherence

• **Summary**
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• Summary
Precursor discovery
Precursor discovery

Distance to touchdown: 3mi to 0mi

Altitude: 3000 to 500

Runway: 0mi
Precursor discovery

- 1000 ft, ~3 miles out
- Speed Exceedance
- Airspeed > threshold

Distance to touchdown
Runway
Precursor discovery

~ 2500ft, 10 miles out
- Turn to final
  - Engine speed unusually high
  - Autopilot Mode mismatch

~ 1500ft, 5 miles out
- Final Flaps not set
  - Tailwinds high

~ 2700ft, 15 miles out
All variables normal

~ 2500ft, 5 miles out
- Engine speed reduced
  - Flaps half way down

Runway

Speed Exceedance

Distance to touchdown  3mi  0mi
Precursor discovery

Data from one flight

~ 2500ft, 10 miles out
- Turn to final
- Engine speed unusually high
- Autopilot Mode mismatch

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Runway

Speed Exceedance

Distance to touchdown

3mi

0mi
Precursor discovery

Precursors
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Runway
3mi        0mi

Distance to touchdown

Speed Exceedance
Precursor discovery

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Speed Exceedance

Flight timeline

Probability of speed exceedance

Precursors

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Probability of speed exceedance
Precursor discovery

**Precursors**

- ~ 2500ft, 10 miles out
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- ~ 2700ft, 15 miles out
  - All variables normal

**Corrections**

- ~ 2500ft, 5 miles out
  - Engine speed reduced
  - Flaps half way down

**Precursors**

- ~ 1500ft, 5 miles out
  - Final Flaps not set
  - Tailwinds high

**Speed Exceedance**
Precursor discovery

Adverse event may be any event of interest
- **Single flight** safety events such as exceedances, go-around, stall,
- **Multi-flight** safety events such as loss of separation, TCAS events,
- **Airspace** or NAS level events such as GDP, congested sectors, delays,
- **Performance** events such as high throughput, mission success,
Why find precursors?

Forensic analysis of past events

- Accident investigation
- Hazard identification
- Operations

Precursors

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Precursors

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Speed Exceedance
Why find precursors?

Real-time decision support

– Crew alerting, Situational awareness, Action recommendation
Why find precursors?

• **Forecasting adverse events better and earlier**
  – Generate a knowledge base (precursors)

• **Develop decision support tools**
  – Alerting systems
  – Recommendation systems on corrective actions

• **Improve operator training**
  – Response and recovery from precursors

• **Predictive maintenance**
  – Precursors to component failures
Challenges in Precursor Discovery

• **Human expert analysis is not scalable**
  – Not easy to find patterns in 100s of time series.
  – Visualization is almost impossible.
  – Subjective variations among experts
  – Costly and slow

• **Data mining is not easy**
  – High dimensions (100s of variables)
  – High velocity of data (1000s of flights per day)
  – Data heterogeneity (continuous, categorical, text, voice, video)
  – Precursors are unlabeled.
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• **Summary**
Anatomy of a Safety Event

Scenario = (Context, Behavior, Outcome)
Precursor discovery using data

Data matrix 
$[X]_{d \times L}$

Start of adverse event

Time: 1 2 3 . . . . . . k . . . . . . L L + 1 . . . T

Event at time k

$\begin{bmatrix}
  x_1(k) \\
  x_2(k) \\
  \vdots \\
  x_d(k)
\end{bmatrix}$
Problem setup

• Data
  – Adverse time series data $\overline{N} = \{X_i\}, \ i = 1, 2, \ldots \overline{N}$;
  – Nominal time series data $N = \{X_i\}, \ i = 1, 2, \ldots N$;
  – Unsupervised

• Event
  – A time slice of data $\left[\begin{array}{c}
x_1(k) \\
x_2(k) \\
\vdots \\
x_d(k)
\end{array}\right]$

  – Data is a sequence of events $X_i = [x(1), x(2), \ldots, x(L_i)]_i$
Given a sequence of events \( X = [x(1), x(2), \ldots, x(L)] \), an action is any state transition \( a_k : x(k) \rightarrow x(k + 1) \) where \( 1 \leq k \leq L \), then \( a_k \) is a precursor to \( E_A \) if

\[
V(a_k) - V(a^*_k) > \delta.
\]

where \( \delta > 0 \),

\( a^*_k \) is the expert’s action at \( k \),

\( V(z) \) is the value function \( \propto P(E_A|z) \)
Related work

• Precursor discovery in multivariate time series is a new problem
  – No direct algorithm exists

Challenges
  1. Unsupervised (no ground truth on precursors)
  2. Temporal (long sequences make it hard)
  3. High dimensionality

Possible approaches

Rule Mining
Temporal rule mining
[1,2] ①②
Motif mining [7] ①②
Clustering [10] ③

Model Based
HMM [9] ①②
Utility based rules [8] ①②

Causality
Causal Bayesian models, Granger causality
[3,4,5,6] ①②

Issues/Drawbacks
  ① Computationally expensive (scales combinatorial/exponential with number of items).
  ② Doesn’t handle continuous data (or needs discretization which grows combinatorial).
  ③ Similarity metric not easy to define for high dimensional data.
References


An MDP is a tuple \((\mathcal{S}, \mathcal{A}, P_{s,a}, \gamma, R)\)

- \(\mathcal{S} = \mathbb{R}^d\) is a continuous state space with \(d\) state variables,

- \(\mathcal{A} = \mathbb{R}^l\) is an action space with \(l\) action variables,

- \(\{P_{s,s'}^a\}\) (or \(P_{ss'}\) if actions are unknown) are the state transition probabilities,

- \(\gamma \in [0, 1]\) is the discount factor,

- \(R : \mathcal{S} \rightarrow \mathbb{R}\) is the underlying reward function,

policy: \(\pi(s, a) = p(a|s)\),

optimal policy: \(\pi_E(s) = a^*\),
The value of state $x_0$ under policy $\pi$ is 
$$V^\pi(x_0) = E[R(x_0) + \gamma R(x_1) + .. + \gamma^L R(x_L)|\pi]$$
where the expectation is over the distribution of sequences starting from $x_0$.

The expert’s policy $\pi_E$
$$\pi_E(x) \geq \pi_i(x) \iff V^{\pi_E}(x) \geq V^{\pi_i}(x) \forall \pi_i$$

Bellman’s optimality
$$\pi_E(x_k) = \text{arg max}_{\text{feasible } x_{k+1}} V^{\pi_E}(x_{k+1})$$
ADOPT Framework

1. Time series database
   - Adverse time series, \( \mathcal{N} \)
   - Nominal time series, \( \mathcal{N}^* \)

2. Inverse Reinforcement Learning
   - Expert's reward model, \( \hat{R}(s) \)

3. Precursor Discovery
   - Expert's value model, \( \hat{V}^{\pi_E}(s) \)

Precursors \( P_{EA} \)
Step 1: Expert’s Reward Model

- $R(x; \alpha) = \alpha_1 \phi_1(x) + \alpha_2 \phi_2(x) + \ldots + \alpha_m \phi_m(x)$
  - A general model of the expert’s reward
  - $\alpha = [\alpha_1 \quad \alpha_2 \quad \ldots \quad \alpha_m]^T$ to be estimated
  - $\phi_i(x); i = 1, 2, \ldots, m$ are some known basis functions (gaussian)

- $\alpha^* = \arg \min_{\alpha} \{E_{x_0}[V^{\pi_{adv}}(x_0; \alpha)] - E_{x_0}[V^{\pi_E}(x_0; \alpha)]\}$
  - such that $|\alpha_i| \leq 1, i = 1, 1, \ldots, m$

$$\hat{R}(x) = f_R(x; \alpha^*) = \sum_{i=1}^{m} \alpha_i^* \phi_i(x)$$

ADOPT Framework

Time series database

Adverse time series, \( \mathcal{N} \)

Nominal time series, \( \mathcal{N}' \)

Inverse Reinforcement Learning

Expert’s reward model, \( \hat{R}(s) \)

Precursor Discovery

Precursors \( P_{EA} \)

Reinforcement Learning

Expert’s value model, \( \hat{V}_{\pi_E}(s) \)
Step 2: Expert’s Value Model

- Value estimation by Monte Carlo method
  - Known reward (from previous step)
  - Time series data as Monte Carlo samples
  - Return $\text{Ret}(\mathbf{x}) = \sum \gamma^k R(\mathbf{x}_k)$ for each state $\mathbf{x}$ as accumulated rewards

- For every labeled pair $(\mathbf{x}_i, \text{Ret}(\mathbf{x}_i))$, a regression model $\hat{V}^{\pi_E}(\mathbf{x}; \theta)$ parameterized by $\theta$ can be built
  - $\theta^* = \arg\min_{\theta} \frac{1}{N_s} \sum_{i=1}^{N_s} \| \text{Ret}(\mathbf{x}_i) - \hat{V}^{\pi_E}(\mathbf{x}_i; \theta) \|^2 + \frac{\mu}{2} \| \theta \|^2$

$$\hat{V}^{\pi_E}(\mathbf{x}) = f_V(\mathbf{x}; \theta^*)$$
Step 3: Precursor Discovery

Given a sequence of events \( X = [x(1), x(2), .., x(L)] \), an action is any state transition \( a_k : x(k) \rightarrow x(k + 1) \) where \( 1 \leq k \leq L \), then \( a_k \) is a precursor to \( E_A \) if

\[
V(a_k^*) - V(a_k) > \delta.
\]

- requires finding the “optimal” decision
  - Bellman’s optimality
    \[
x_{k+1}^* = \arg \max \{ \text{feasible } x_{k+1} \} \ V^{\pi_E}(x_{k+1})
\]

- requires scoring the suboptimal decisions
  - \( PI_k = V^{\pi_E}(x_{k+1}^*) - V^{\pi_E}(x_{k+1}) \)
  - A weighted contribution from reward may be added to tradeoff short term vs long term precursors
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• Summary
Take-off Stall Hazard

Adverse event: Drop in airspeed after take-off by at least a 20 knots

Goal: To find precursors using flight recorded data

![Graph showing Adverse flight trajectories and Nominal Distribution over time after liftoff.](image)
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Factors affecting drop in airspeed

• **Human Factors**
  – Errors in reference speed calculations, estimating AC weight, energy management.
  – human-machine interactions, fatigue, aggressive flying, mode confusion.

• **Environmental**
  – Tail winds, wind shear, sensor failure

• **Procedural**
  – Avoiding terrain, flying over restricted area
ADOPT analysis

400 nominal flights
400 adverse flights
200 (100+100) holdout set

Time series database

Nominal time series, $\mathcal{N}^n$

Adverse time series, $\mathcal{N}$

Inverse Reinforcement Learning

Test trajectory $X_T \in \mathcal{N}$

# basis functions: 5000
Spread of Gaussian: 0.05

Precursor Discovery

SVM

Expert's value model, $\hat{V}^{\pi_E}(s)$

Precursors $P_{EA}$
Flight analysis 1 – reference speed set incorrectly
Flight analysis 2 – reference speed set incorrectly

<table>
<thead>
<tr>
<th>Time</th>
<th>Pitch Angle</th>
<th>Tailwind</th>
<th>Altitude</th>
<th>Roll Angle</th>
<th>Auto-throttle</th>
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<td>1s</td>
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<td>Pitch Angle</td>
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<td>25s</td>
<td>Pitch Angle</td>
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</tr>
</tbody>
</table>

**Altitude**

**Roll Angle**

**Pitch Angle**

**Tailwind**

**Auto-throttle**

**PFD Spd**

**Precursor index (PI)**
Flight analysis 1 – Nominal Flight
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• Summary
STAR procedure adherence

Adverse event: Drop in airspeed after take-off by at least a 20 knots

Goal: To find precursors using flight recorded data
Adverse event: Drop in airspeed after take-off by at least a 20 knots

Goal: To find precursors using flight recorded data
ADOPT analysis

400 nominal flights
400 adverse flights
200 (100+100) holdout set

Time series database

Nominal time series, $\mathcal{N}$

Adverse time series, $\mathcal{N}^*$

Inverse Reinforcement Learning

Test trajectory

$X_T \in \mathcal{N}$

# basis functions: 5000
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Expert's reward model, $\hat{R}(s)$

Precursor Discovery

Reinforcement Learning

Expert's value model, $\hat{V}^\pi_E(s)$

SVM

Precursors $\Rightarrow P_{EA}$
Flight analysis 1 – reference speed set incorrectly

<table>
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<th>20s</th>
<th>25s</th>
<th>30s</th>
<th>35s</th>
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<tr>
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<tr>
<td>Roll Angle</td>
<td>Autopilot</td>
<td>Roll Angle</td>
<td>Roll Angle</td>
<td>Auto-throttle</td>
</tr>
<tr>
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<td>Tailwind</td>
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<td>Roll Angle</td>
</tr>
<tr>
<td>Altitude</td>
<td>PFD Spd</td>
<td>PFD Spd</td>
<td>Pitch Angle</td>
<td>Tailwind</td>
</tr>
<tr>
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<td>Tailwind</td>
<td>Auto-throttle</td>
<td>Tailwind</td>
<td>Pitch Angle</td>
</tr>
</tbody>
</table>
Flight analysis 2 – reference speed set incorrectly

<table>
<thead>
<tr>
<th>P</th>
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<th>Jo</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Slope-possible</td>
<td>Slope-possible</td>
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<td>Ground Spd</td>
<td>Descent Rate</td>
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<td>Descent Rate</td>
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ADOPT’s features

• Data mining based precursor discovery algorithm

• Input
  – Feed in time series data with adverse event
  – Feed in nominal time series data
  – Data could be continuous, categorical, text, images

• Output
  – Precursor time instants
  – Precursor variables
  – Probability score

• Correlation and not Causation
ADOPT’s features

- Use any/all domain knowledge
  - Selecting variables
  - Scoping problems in space, time
  - Hand-engineering features

- Use any classifier of choice
  - SVM, decision tree, K-NN, logistic regression

- Extends to multiple adverse events
  - Holistic analysis, safety margins

- Parallelizable
  - Multiple CPUs
  - Analyze multiple airports, airspaces, aircrafts in parallel
Summary

• Precursor discovery is an important problem with uses in multiple applications in Aviation.

• ADOPT is an efficient data mining solution to find precursors.

• Two case studies are presented to show the setup, working and features of ADOPT.

• ADOPT will be open-sourced in the near future.
Thank You