Machine Learning Applications for Veer-Off Prediction During Landing

14th May 2019

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Aircraft Performance

AIRBUS DEFENCE & SPACE

Singapore Airlines - BOEING - B777-300ER (9V-SWQ) flight
SQ327
Aviation Accidents Database

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Contents

Introduction - Aim and Objectives

- A **veer-off** is a lateral runway excursion, in which the aircraft deviates from the intended path (centerline) and departs the runway laterally, over the runway shoulders.

- The **aim** is to **implement a supervised machine learning algorithm**, capable of generating a <u>**hypothesis**</u> which <u>**predicts**</u> if a certain **landing** operation will result in a **veer-off** or not.

- The prediction will be based on:
  - Environmental Conditions.
  - Operational Factors.

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Introduction - Aim and Objectives

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But, first of all… WHY?

Why…

… veer-off?

… landing?

… machine learning?

But, first of all… WHY?

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… veer-off?

… landing?

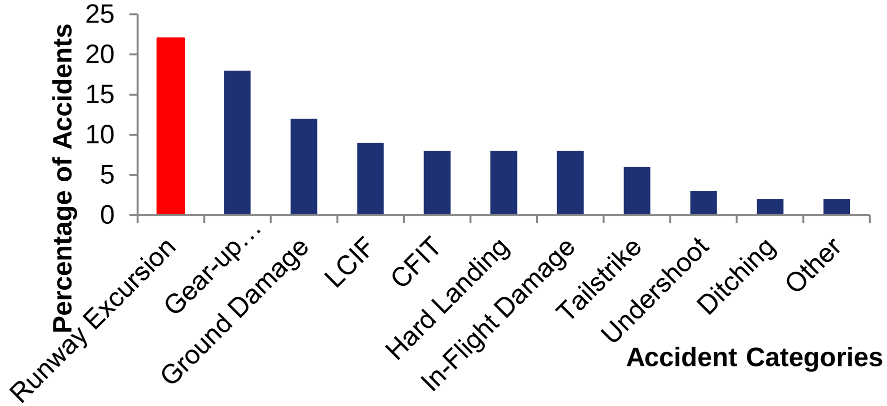
… machine learning?

But, first of all… WHY?

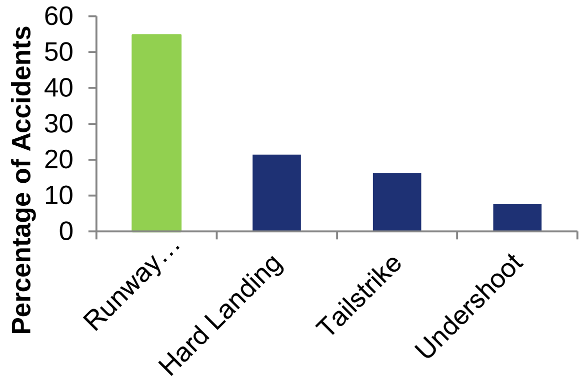
- WHY **veer-off**?

In the 2010-2014 period*, <u>Runway Excursions</u> were:

- The most frequent type of accident (**22%**) **overall**.



- The most frequent type of **runway safety-related** accident (**54.7%**)



Source: Runway Safety Accident Analysis Report (IATA)

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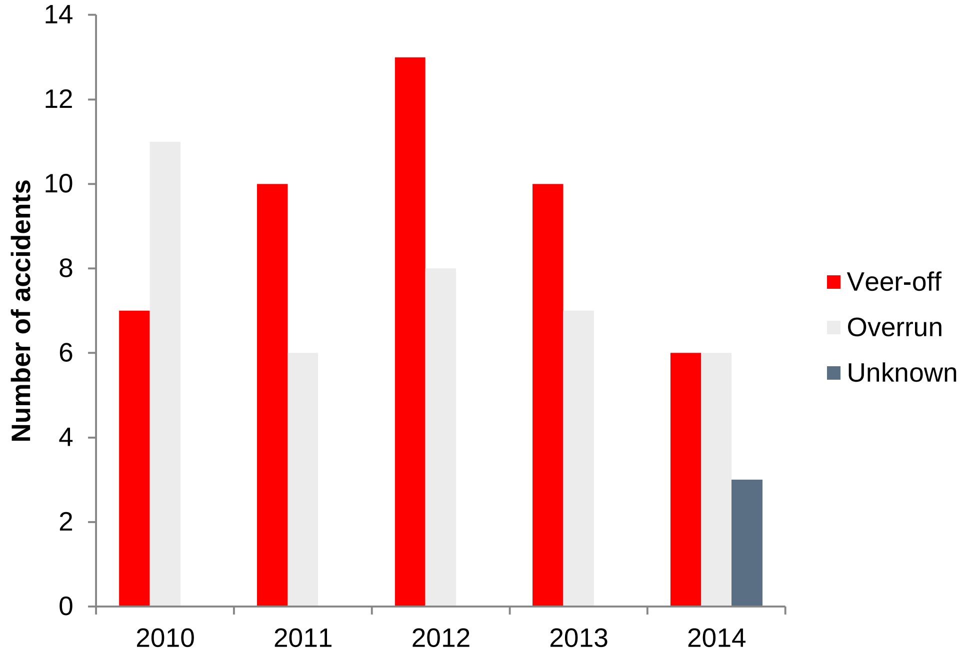
But, first of all… WHY?

- WHY **veer-off**?

In the 2010-2014 period*:

- **Veer-offs** comprised **52.9%** of runway excursion accidents.

Source: Runway Safety Accident Analysis Report (IATA)



But, first of all… WHY?

Why…

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But, first of all… WHY?

- WHY **landing**?

Runway Excursion Type	Number of Accidents	Phase of Flight	Number of Fatal Accidents
Overrun	1	Take-off	0
Overrun	35	Landing	5
Overrun	2	Rejected Take Off	0
Veer-offs	5	Take-off	0
Veer-offs	41	Landing	0

Table 2: Comparison Frequency of Runway Excursion Types for the Different Phases of Flight

But, first of all… WHY?

- WHY **landing**?

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52.9%

Table 2: Comparison Frequency of Runway Excursion Types for the Different Phases of Flight

But, first of all… WHY?

- WHY **landing**?

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Veer-offs	41	Landing	0

Table 2: Comparison Frequency of Runway Excursion Types for the Different Phases of Flight

In the 2010-2014 period*:

- **Almost 90%** of veer-off accidents took place during landing phase.

Source: Runway Safety Accident Analysis Report (IATA)

Nevertheless, bear in mind…

- Veer-offs are, **in absolute terms**, infrequent: between 1995-2008, only 174 veer-off incidents **worldwide** (in average, 13 accidents/year).
  - A great **class imbalance** might be expected (normal landings highly outnumber veer-offs)

But, first of all… WHY?

Why…

… veer-off?

… landing?

… machine learning?

But, first of all… WHY?

- WHY **Machine Learning**?

Two questions come to mind:

- Which **combination of factors** is likely to lead to a veer-off?

- Is it possible to know **beforehand** if a certain landing operation is prone to experiencing a veer-off?

But, first of all… WHY?

- WHY **Machine Learning**?

Two questions come to mind:

- Which **combination of factors** is likely to lead to a veer-off?
- Is it possible to **predict** if a certain landing operation is prone to experiencing a veer-off?

How can we answer these?

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But, first of all… WHY?

- WHY **Machine Learning**?

Two questions come to mind:

- Which **combination of factors** is likely to lead to a veer-off?
- Is it possible to **predict** if a certain landing operation is prone to experiencing a veer-off?

How can we answer these?

MACHINE LEARNING

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Contents

Introduction to Machine Learning

Concept

- **Machine Learning** is application of artificial intelligence, which **trains** computers to "learn" from data they are fed with.

- Once this training process is completed, computers attain the ability to make **predictions** based on the knowledge they have acquired.

Introduction to Machine Learning

Concept

- **Machine Learning** is application of artificial intelligence, which **trains** computers to "learn" from data they are fed with.

- The data used to "teach" the learning algorithm constitutes the **training set**.
  - Each component of the training set is denoted as a **training example**.
  - Each training example is composed by a number of parameters, or **features**, which describe it.

How does this apply to our case?

- In supervised learning, features can be of two types:
  - **Predictor** features: descriptive.
  - **Class** features: classification drivers.

- Once this training process is completed, computers attain the ability to make **predictions** based on the knowledge they have acquired.

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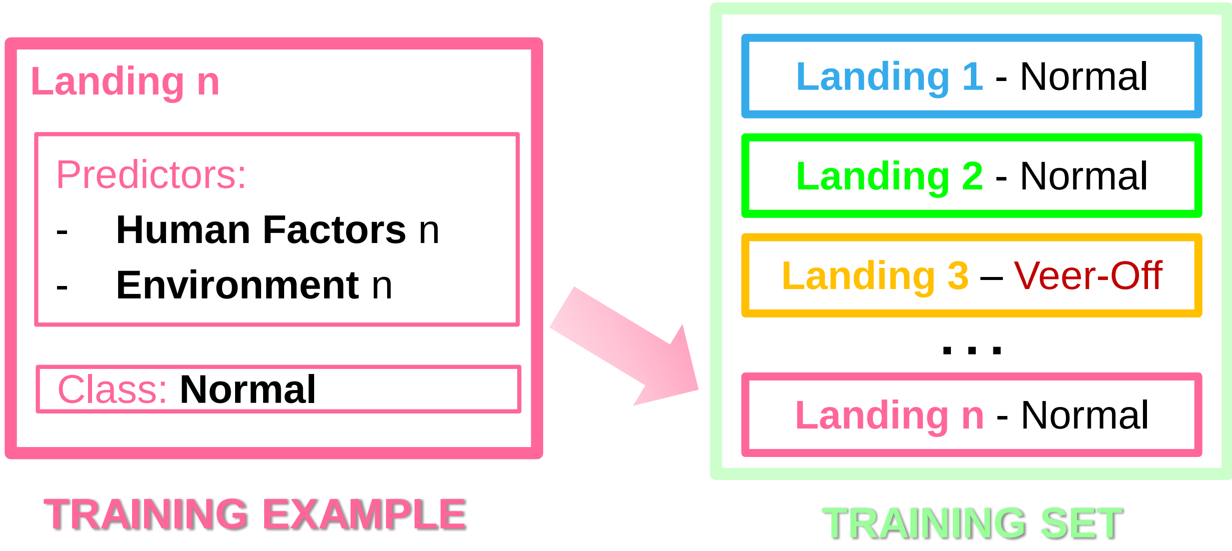
Introduction to Machine Learning

Application to Veer-Off Prediction: Data

- **TRAINING SET:** Collection of landing operations.
- Each **individual** landing operation constitutes a **TRAINING EXAMPLE**.
- The **FEATURES** that describe each landing operation can be:
  - **PREDICTORS**: **Human Factors** and **Environment**.
  - **CLASS**: Landing Status (**Normal Landing/Veer-Off**).



Introduction to Machine Learning

Concept

MACHINE LEARNING ALGORITHM

HYPOTHESIS

Introduction to Machine Learning

Concept

MACHINE LEARNING ALGORITHM

Learning strategy

HYPOTHESIS

Outcome of the ML algorithm

Allows us to effectively predict

Introduction to Machine Learning

Concept

MACHINE LEARNING ALGORITHM

Learning strategy

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Outcome of the ML algorithm

Allows us to effectively predict

Let’s focus on 3 key aspects:

- Landing dataset for training/testing
- Learning Algorithm selection
- Hypothesis

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- **Landing dataset for training/testing**
- Learning Algorithm selection
- Hypothesis

Landing dataset for training/testing

Introduction

- Landing operations database, compiled by Cranfield University.
- **46720 landings**
- Each operation: **34 features**.

Landing dataset for training/testing

Predictors

OPERATION → - **AIRCRAFT**

- DIRECTIONAL CONTROL MEANS
- TOUCHDOWN VALUES
- APPROACH
- ACCELERATION
- TIME TO APPL. STOPPING MEANS
- BRAKING
- THRUST

ENVIRONMENT →

- **OPERATIONAL CONDITIONS**
  - VISIBILITY
  - RUNWAY CONDITION
  - WIND (including GUST)
- **ASYMMETRY TRIGGERS**
- **INADEQUATE INFO TO CREW**

Landing dataset for training/testing

Predictors

OPERATION	Parameter	Units
DIRECTIONAL CONTROL MEANS	Maximum Rudder Deflection	o
	Minimum Rudder Deflection	o
	Maximum Nose Wheel Steering Deflection	o
	Minimum Nose Wheel Steering Deflection	o
	Magnitude of Braking Asymmetry	
TOUCHDOWN VALUES	Flap Deflection at Touchdown	o
	Pitch Angle at Touchdown	o
	Roll Angle at Touchdown	o
	True Ground Speed at Touchdown	kt
	True Airspeed at Touchdown	kt
APPROACH	Glideslope Deviation at 150 ft RALT	dots
	Glideslope Deviation at 50 ft RALT	dots
	Difference between actual and target speed at 50 ft radio height	kt
	Maximum normal acceleration at landing	g
ACCELERATION (LAT AND LONG)	Average Lateral Acceleration (ground phase)	g
	Average Longitudinal Acceleration (ground phase)	g
TIME TO APPLICATION OF STOPPING MEANS	Time to Reverse Deployment	s
	Time to Spoiler Deflection	s
	Time to first Brake Pedal Input	s
BRAKING	Autobrake Setting	CAT: LOW/MED/MAX
	Mean Total Brake Pedal Input	Brake Pedal Input Units
THRUST	Idle Thrust at Touchdown	CAT: YES/NO
	Mean N1 (left and right engines): overall thrust	% rpm
	Duration of Thrust Assymetry	s
	Magnitude of Thrust Asymmetry	% rpm

Landing dataset for training/testing

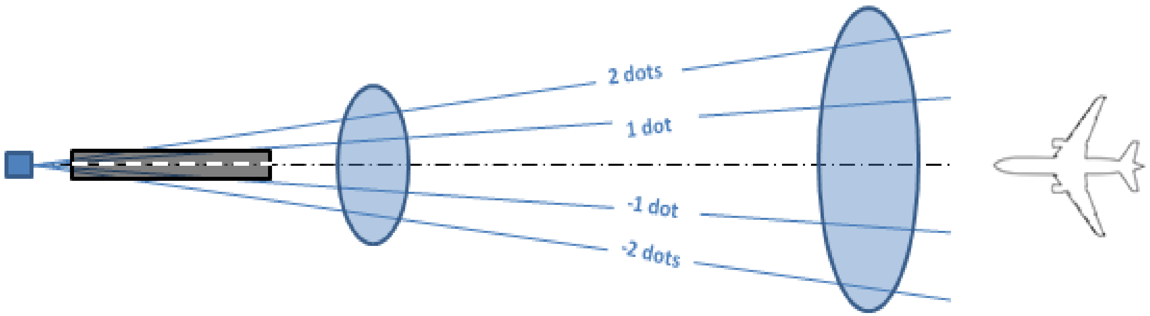
Predictors

ENVIRONMENT	Parameter	Units
OPERATIONAL CONDITIONS	Visibility	Km
	Runway Condition	CAT: DRY/WET
	METAR Headwind Gust Intensity	kt
	Recorded Headwind	kt
ASYMMETRY TRIGGERS	Heading Deviation	º
	Recorded Crosswind	kt
	METAR Crosswind Gust Intensity	kt
INADEQUATE CREW INFO	Difference between recorded and METAR headwind	kt
	Difference between recorded and METAR crosswind	kt

Landing dataset for training/testing

Introduction

- <u>The interest is to predict when a **certain landing will result in veer-off.**</u>
- The only feature in the original database that allows to detect the presence of a veer-off is **localizer deviation:**
  - **CLASS:** derived from **localizer deviation** values.
  - **PREDICTORS:** remaining features.
- Localizer system:



The units of angular deviation are **dots** (in this case, 1dot = 0.04º)

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Landing dataset for training/testing

Class

- As provided by Cranfield University, the examples in the operations database are **not** classified in advance:
  - Adequate **labelling** of examples (as deviated or un-deviated) is mandatory before the learning algorithm is set- up.
  - The only variable that allows to evaluate lateral deviation is **localizer deviation**.

- This leaves:
  - **144 veer-offs**
    - 68 right
    - 76 left
  - **46576 normal landings**

Only **0.3%** of operations are veer-offs:

<u>Extreme class imbalance</u>

Let’s focus on 3 key aspects:

- Landing dataset for training/testing
- **Learning Algorithm selection**
- Hypothesis

Learning Algorithm Selection

Necessities

- The selection of an adequate learning scheme must be **driven** by the particularities of the problem to solve.

- **<u>Class imbalance</u>** is the **most critical condition**:
  - Only **a few benchmarks** are capable of generating robust classification hypotheses when trained with highly skewed sets.

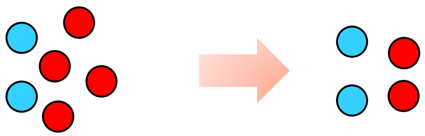
Learning Algorithm Selection

RUSBoost

- The implemented routine was **RUSBoost**.

- RUSBoost is a **hybrid** benchmark, that merges a **Random Undersampling (RUS)** routine with an **AdaBoostM2 algorithm**.

  - **RUS** is the **aleatory removal of examples from the majority class**. Its target is to achieve **artificial class balance**.



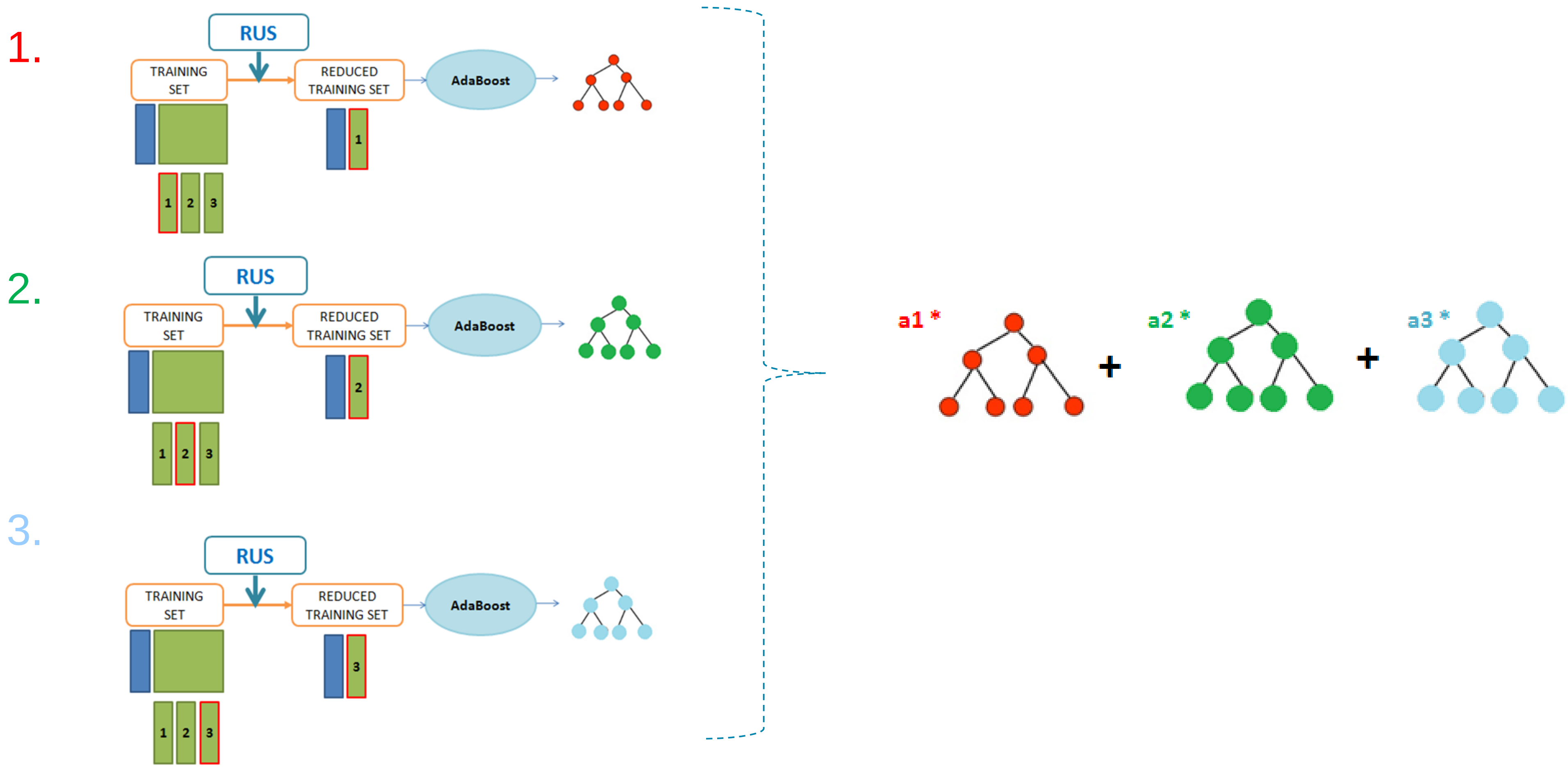
  - **AdaBoost** (**Ada**ptative **Boost**ing) consists in training **sequentially** a certain number of decision trees. The final hypothesis is the **weighted sum** of all trees.

Learning Algorithm Selection

RUSBoost Schematic Representation

<u>Step 1. RUS+AdaBoost Iterations</u>

<u>Step 2. Hypothesis generation</u>



Let’s focus on 3 key aspects:

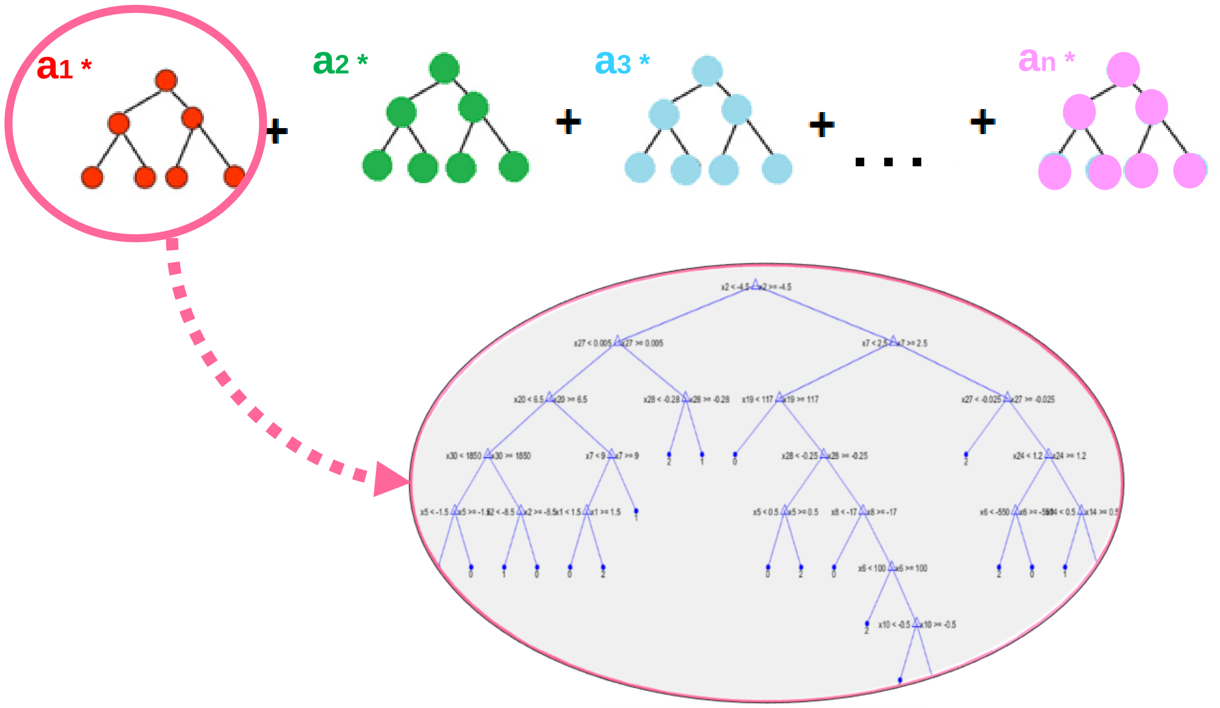
- Landing dataset for training/testing
- Learning Algorithm selection
- **Hypothesis**

Hypothesis

– The final hypothesis is a **linear combination of decision trees.**

– Each tree has an associated **weight**: the higher their weight, the higher the predictive capability of the tree.

Hypothesis =



1. Introduction - Aim and Objectives

2. RUSBoost: Machine Learning Application for Veer-Off Prediction

3. **Hypothesis Results**
   a) **Success Rate in Veer-Off Prediction**
   b) Pattern Identification
   c) Compensation effects

4. Key Benefits

Success Rate in Veer-Off Prediction

- Hypothesis quality is to be assessed from two points of view:
  - **Success rate** (= % of veer-offs correctly identified as such) and FP rate (=% of normal operations
  - **Patterns extracted**

Success Rate in Veer-Off Preduction

– We have used four different hypothesis, in order to predict:

Left Veer-Off	**Right Veer-Off**	**Veer-Off (general, no side distinction)**	**Left and Right Veer-Off (including side distinction)**

Success Rate in Veer-Off Prediction

– When applied to **novelty data**, the results are:

Left Veer-Off	**Right Veer-Off**	**Veer-Off (general, no side distinction)**	**Left and Right Veer-Off (including side distinction)**

• **Success Rate: 71%**
• **FP Rate: 14.5%**
	• **Success Rate: 70.6%**
	• **FP Rate = 4.4%**
		• **Success Rate: 73.6%**
		• **FP Rate: 8.7%**
			• **Success Rate:**
			  • **Right: 76.5%**
			  • **Left: 78.9%**
			• **FP Rate: 26.5%**

Success Rate in Veer-Off Prediction

– Selection of best predictive hypothesis

BEST Success Rate

EXCESSIVE FP Rate

Left and Right Veer-Off (including side distinction)

- **Success Rate:**
  - **Right: 76.5%**
  - **Left: 78.9%**

- **FP Rate: 26.5%**

Success Rate in Veer-Off Prediction

– Selection of best predictive hypothesis

BEST compromise

Veer-Off (general, no side distinction)

- **Success Rate: 73.6%**
- **FP Rate: 8.7%**

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   a) Success Rate in Veer-Off Prediction

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4. Key Benefits

Pattern Identification

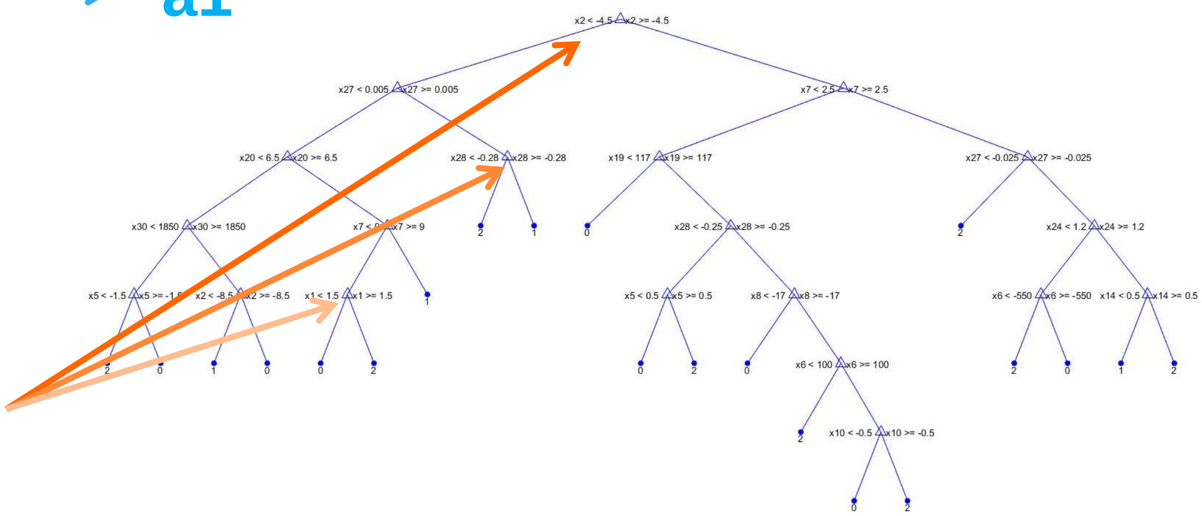
– The generated hypothesis allows to establish the **most important variables for the prediction of a veer-off**, on **three** levels:

1. **Tree weighting factor** → **a1 ***

↑ weight → ↑ relevance of associated decision paths

2. **Most used variables**

3. **Hierarchy the variables** in each tree



Pattern Identification: Hierarchy of Predictors

% of trees

100%
- High average lateral acceleration (ground phase)
- Crosswind

85%
- Residual crab
- Glideslope deviation at 50 ft RALT

70%
- Insufficient rudder deflection
- TAS at TD
- Early reverse deployment

60%
- Braking asymmetry
- Difference recorded/METAR wind measurements

40%
- High difference between actual/target speed at 50 ft radio height

35%
- Thrust asymmetry
- Low Visibility

20% or less
- Time to spoiler deflection
- Low normal acceleration at TD (*kiss landing*)
- Low Autobrake Setting

Pattern Identification : Hierarchy of Predictors

% of trees

100%

- High average lateral acceleration (ground phase)
- **Crosswind**

Leading Node in 90% of trees in the hypothesis

85%

- Residual crab
- Glideslope deviation at 50 ft RALT

70%

- Insufficient rudder deflection
- TAS at TD
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Combinations of factors that might result in veer-off

% of trees

100%
- **High average lateral acceleration (ground phase)**
- **Crosswind**

85%
- **Residual crab**
- **Glideslope deviation at 50 ft RALT**

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71% of trees

Combinations of factors that might result in veer-off

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100%

- **High average lateral acceleration (ground phase)**
- **Crosswind**

85%

- Residual crab
- **Glideslope deviation at 50 ft RALT**

70%

- Insufficient rudder deflection
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- **Early reverse deployment**

60%

- Braking asymmetry
- Difference recorded/METAR wind measurements

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35%

- Thrust asymmetry
- Low Visibility

20% or less

- Time to spoiler deflection
- Low normal acceleration at TD (*kiss landing*)
- Low Autobrake Setting

64 % of trees

Combinations of factors that might result in veer-off

<u>**% of trees**</u>	
100%	– **High average lateral acceleration (ground phase)** – **Crosswind**
85%	– **Residual crab** – Glideslope deviation at 50 ft RALT
70%	– Insufficient rudder deflection – TAS at TD – **Early reverse deployment**
60%	– Braking asymmetry – Difference recorded/METAR wind measurements
40%	– High difference between actual/target speed at 50 ft radio height
35%	– Thrust asymmetry – Low Visibility
20% or less	– Time to spoiler deflection – Low normal acceleration at TD (*kiss landing*) – Low Autobrake Setting

57 %
of trees

Combinations of factors that might result in veer-off

% of trees

% of trees	Factors
100%	**– High average lateral acceleration (ground phase)** **– Crosswind**
85%	– Residual crab – Glideslope deviation at 50 ft RALT
70%	– Insufficient rudder deflection – TAS at TD **– Early reverse deployment**
60%	– Braking asymmetry **– Difference recorded/METAR wind measurements**
40%	– High difference between actual/target speed at 50 ft radio height
35%	– Thrust asymmetry – Low Visibility
20% or less	– Time to spoiler deflection – Low normal acceleration at TD (*kiss landing*) – Low Autobrake Setting

40 % of trees

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Combinations of factors that might result in veer-off

% of trees

100%
- **High average lateral acceleration (ground phase)**
- **Crosswind**

85%
- **Residual crab**
- **Glideslope deviation at 50 ft RALT**

70%
- Insufficient rudder deflection
- TAS at TD
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- **Low Visibility**

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35% of trees

Combinations of factors that might result in veer-off

% of trees

% of trees	Factors
100%	**– High average lateral acceleration (ground phase)** **– Crosswind**
85%	**– Residual crab** **– Glideslope deviation at 50 ft RALT**
70%	– Insufficient rudder deflection – TAS at TD – Early reverse deployment
60%	– Braking asymmetry – Difference recorded/METAR wind measurements
40%	– High difference between actual/target speed at 50 ft radio height
35%	**– Thrust asymmetry** **– Low Visibility**
20% or less	– Time to spoiler deflection – Low normal acceleration at TD (*kiss landing*) – Low Autobrake Setting

27% of trees

Combinations of factors that might result in veer-off

% of trees	Factors
100%	– **High average lateral acceleration (ground phase)** – **Crosswind**
85%	– **Residual crab** – **Glideslope deviation at 50 ft RALT**
70%	– Insufficient rudder deflection – **TAS at TD** – Early reverse deployment
60%	– **Braking asymmetry** – Difference recorded/METAR wind measurements
40%	– High difference between actual/target speed at 50 ft radio height
35%	– Thrust asymmetry – Low Visibility
20% or less	– Time to spoiler deflection – Low normal acceleration at TD (*kiss landing*)

50% of trees

Combinations of factors that might result in veer-off

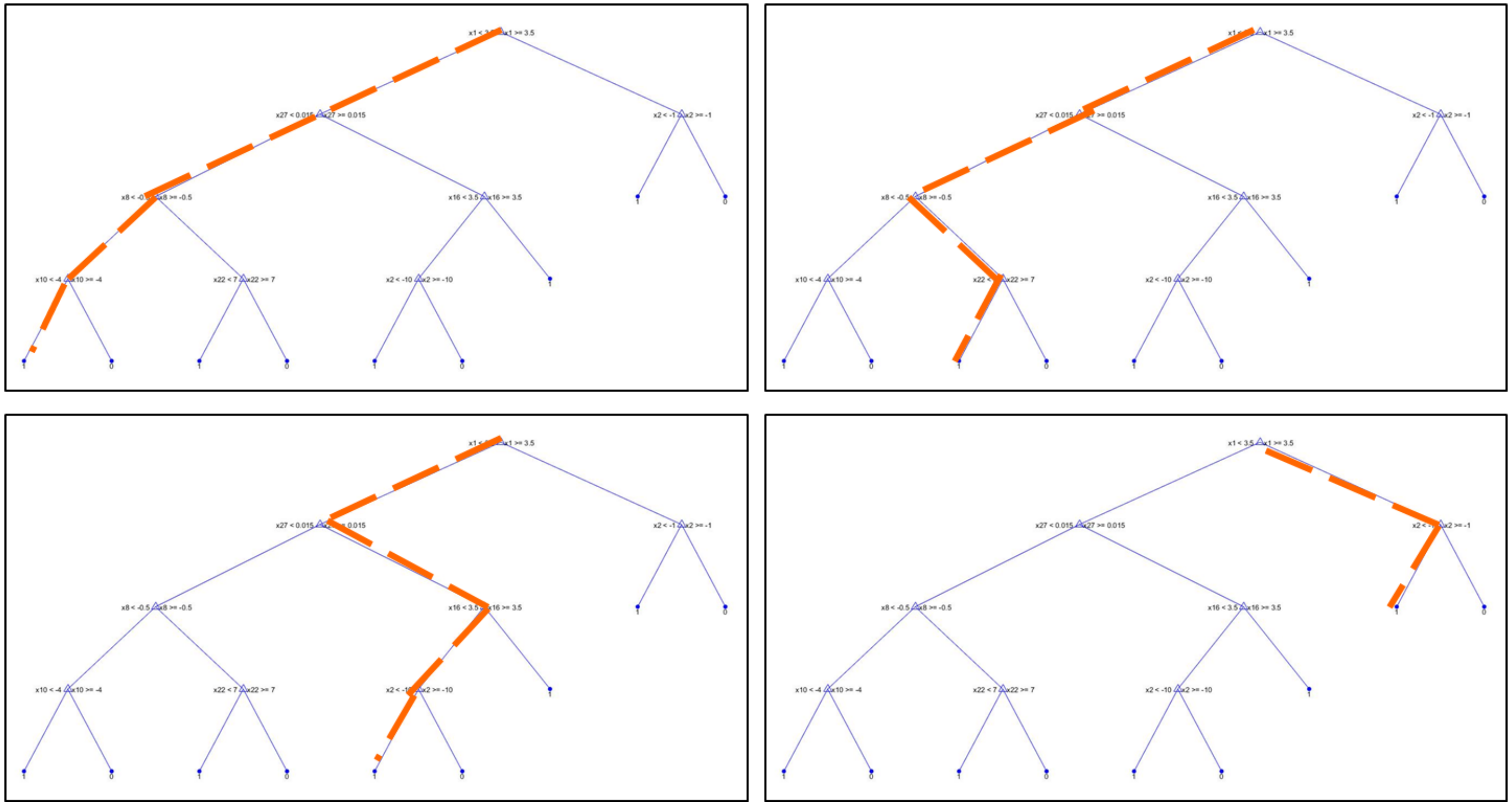
% of trees

% of trees	Factors
100%	**– High average lateral acceleration (ground phase)** **– Crosswind**
85%	**– Residual crab** **– Glideslope deviation at 50 ft RALT**
70%	– Insufficient rudder deflection **– TAS at TD** – Early reverse deployment
60%	– Braking asymmetry – Difference recorded/METAR wind measurements
40%	**– High difference between actual/target speed at 50 ft radio height**
35%	– Thrust asymmetry – Low Visibility
20% or less	– Time to spoiler deflection – Low normal acceleration at TD (*kiss landing*) – Low Autobrake Setting

35% of trees

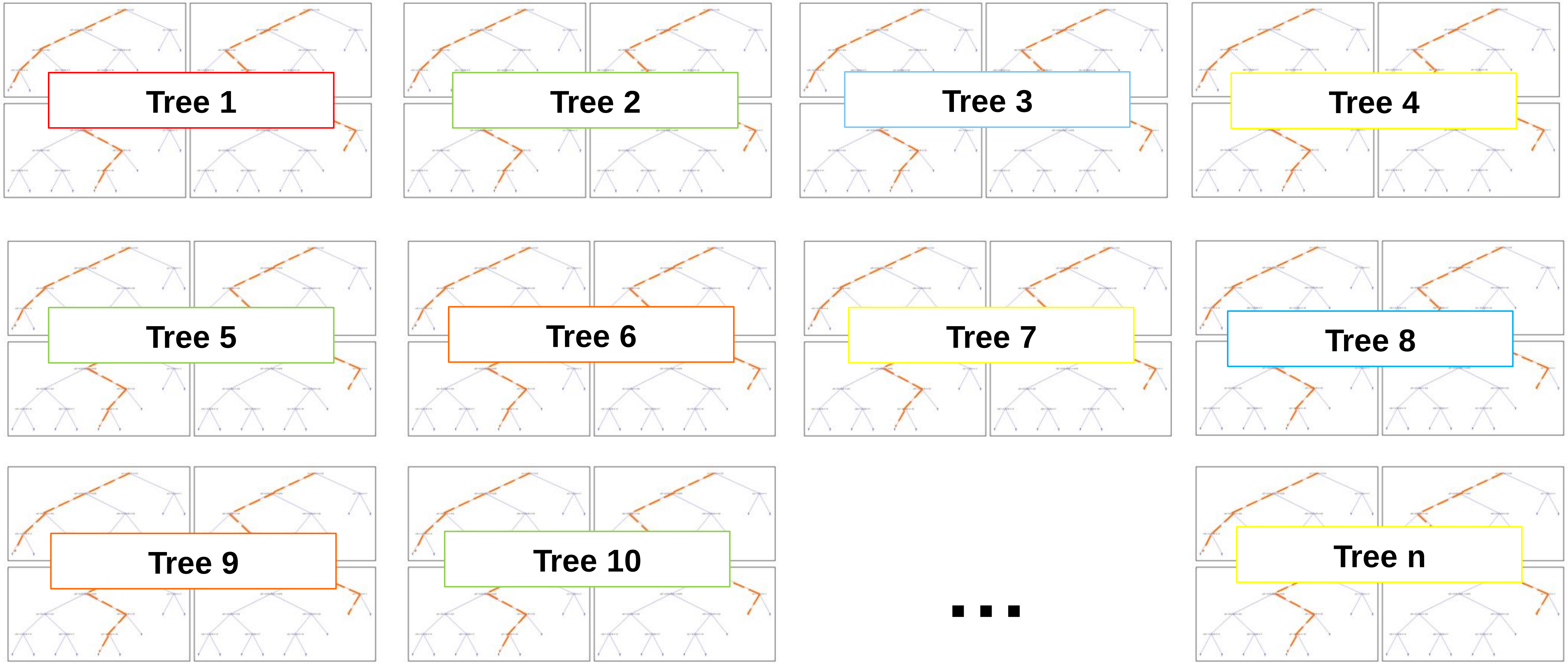
A brief estimation

- Each tree in the hypothesis: several combinations of factors that might result in veer-off



A brief estimation

Hypothesis ~ $10^3 – 10^4$ trees



A brief estimation

- 1000 trees
- 10 veer-off paths/tree

$\sim 10^4$ possible combinations for veer-off

“Compensation” effect

If one condition does not take place, **which others**, added to the pre-existing ones, could also lead to a veer-off?

"Compensation" effect

If one condition does not take place, **which others**, added to the pre-existing ones, could also lead to a veer-off?

Let's see two illustrative examples,extracted from our hypothesis.

“Compensation” effect : Example 1

Ex.1 Combination of conditions that might lead to veer-off (according to RUSBoost generated hypothesis):

- Leading Node: Undesired braking asymmetry
- 2nd Node: Low visibility

VEER-OFF

“Compensation” effect : Example 1

Ex.1 Combination of conditions that might lead to veer-off (according to RUSBoost generated hypothesis):

- Leading Node: Undesired braking asymmetry
- 2nd Node: Good visibility

Normal Landing

“Compensation” effect : Example 1

Ex.1 Combination of conditions that might lead to veer-off (according to RUSBoost generated hypothesis):

- Leading Node: Undesired braking asymmetry
- 2nd Node: Good visibility
- 3rd Node: Thrust asymmetry

$\left.\begin{matrix} \\ \\ \\ \end{matrix}\right\}$ **VEER-OFF**

“Compensation” effect : Example 2

Ex.2 Combination of conditions that might lead to veer-off (according to RUSBoost generated hypothesis):

- Leading Node: Crosswind
- 2nd Node: Low TAS at TD
- 3rd Node: Low difference actual/target speed
  at h=50 ft

Normal Landing

“Compensation” effect : Example 2

Ex.2 Combination of conditions that might lead to veer-off (according to RUSBoost generated hypothesis):

- Leading Node: Crosswind
- 2nd Node: Low TAS at TD
- 3rd Node: Low difference actual/target speed below 50 ft
- 4th Node: Early reverse deployment

$\Big\}$ **VEER-OFF**

“Compensation” effect : Example 2

Ex.2 Combination of conditions that might lead to veer-off (according to RUSBoost generated hypothesis):

- Leading Node: Crosswind
- 2nd Node: Low TAS at TD
- 3rd Node: Low difference actual/target speed below 50 ft
- 4th Node: High Glideslope deviation at 50 ft RALT
- 5th Node: Residual crab

VEER-OFF

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4. Key Benefits

Key Benefits

- This is not meant to be a substitute for traditional FDM methods, but a **complement**, a parallel approach.

- This approach has shown a **good effectivity** in the **prediction** veer-off occurrence.

- It allows to find a great amount of combinations that might lead to a veer-off, as well as compensation effects.

- It constitutes the **first step** to develop **stream data mining** techniques, which would allow a **real-time assessment** of the landing conditions, as well as a **continuous training**.

References

1. **FSF ALAR Briefing Note 8.1**: Runway Excursions.
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