



Al for Weather Forecasting

Development of BI and AI on METAR and TAF data

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Project Introduction

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Sapienza is the oldest university in Rome (founded **1303**), and the largest in Europe: **120,000** students, **3,500** professors.

The **Department of Mechanical and Aerospace Engineering** includes research groups specialized in data science applied to diverse engineering problems.

AGIC aiComply is the Department's technological spin-off, specialized in data intelligence, cloud technologies risk and governance management solutions

Today presentation:

Using advanced Business Intelligence and Artificial Intelligence solutions for <u>weather forecasting management</u>



Disclaimer



The following slides are based on publicly available content, as described in the following papers:

- Patriarca, R., Simone, F., Di Gravio, G. Supporting weather forecasting performance management at aerodromes through anomaly detection and hierarchical clustering (2023) Expert Systems with Applications, 213, art. no. 119210. DOI: 10.1016/j.eswa.2022.119210
- Simone, F., Di Gravio, G., Patriarca, R. Performance-based Analysis of Aerodrome Weather Forecasts (2022) New Trends in Civil Aviation, 2022-October, pp. 27-33. DOI: 10.23919/NTCA55899.2022.9934004

Project Overview



• BACKGROUND •



Weather bulletins
(METAR) are emitted at
regular frequency +
forecasts (TAF) and
special bulletins SPECI

Dedicated **KPIs** defined to capture forecast accuracy





Big-data on text strings of bulletins to be **decoded** first, and then **analysed** systematically

600'000 METAR/SPECI 60'000 TAF

(generic yearly figure)



KPI to be developed for **retrospective** analyses and to generate **proactive** indicators

• NEED •

SOLUTION

User-friendly **systemic dashboards** for the WSP (top management and operational)



ML analysis on KPIs







Customized periodic automatic reporting



Project Aim

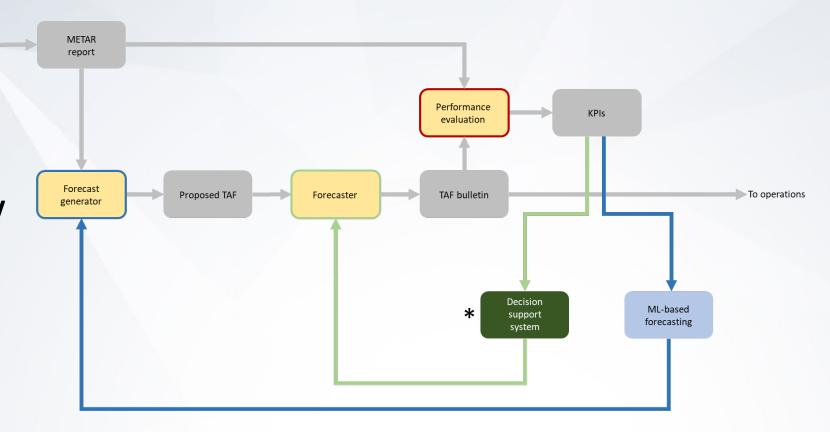


The project aims to:

- --- Forecast weather
- Manage forecast accuracy

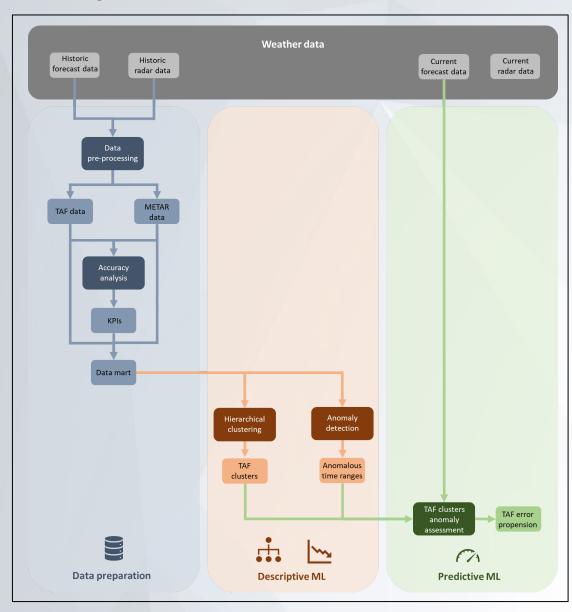
Weather radar

station



Al Pipeline

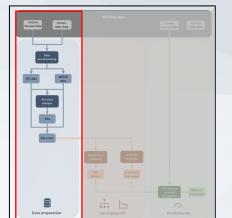




Al pipeline passes through three stages:

- Data Preparation
- Descriptive ML
- Predictive ML

Data Preparation: Decoding Weather Data

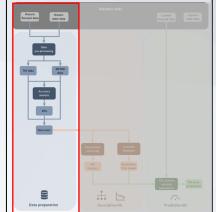




METAR				UTC DATE/TIME
LTFM 241550Z 02022KT 0800 R35R/0800D R17	7L/P1500N R34L/P1500N R36/P1500N SH	SN BLSN SCT002 FEW017CB BKN02	22 M00/M00 Q1025 RETSSN	2022-01-24 15:50:00
LTFM 241520Z 36027G37KT 0800 R35R/0500D				
10 20 30 40 50 60 70	80 90 100 110 120 130 1	40 150 160 170 180 190	0 Q1024 RESHSN BE	2022-01-24 14:50:00
Fly	Check weather	Cancel flight	22 M01/M01 Q1024	2022-01-24 13:50:00
	TAF DECODER		1/M01 Q1024 BECM	2022-01-24 13:20:00
LTFM 241250Z 36023KT 0300 R35R/0	0350D R36/0300D +SHSN	BLSN SCT002 SCT017CB BKN022 N	//00/M00 Q1024 RETSSN BE	2022-01-24 12:50:00
LTFM 241220Z 35022G22	35N R36/0600D +T	SSN BLSN SCT002 SCT017CB BKN0	22 M00/M00 Q1024 RESHS	2022-01-24 12:20:00
LTFM 2411507	4L/0225D R36/14	100U SHSN BLSN SCT002 SCT017CE	3 BKN022 M01/M01 Q1024	2022-01-24 11:50:00
LTFM	34L/0225N R36/0200N +T	SSN BLSN SCT002 SCT017CB BKN0	22 M01/M02 Q1024 RESHS	2022-01-24 11:20:00
	0175N R36/0225N +S	HSN BLSN SCT002 SCT017CB BKN0	22 M01/M02 Q1024 TEMP	2022-01-24 10:50:00
	+L/0325N R36/0300N +S	HSN BLSN SCT003 SCT017CB BKN0	22 M01/M02 Q1024 BECM	2022-01-24 10:20:00
	0275N R34L/0375N R36/0375N +S	HSN SCT003 SCT017CB BKN022 MC	01/M02 Q1024 RETSSN BEC	2022-01-24 09:50:00
	P1500U R34L/1400U R36/P15	500N -SHSN FEW005 FEW018CB BK	(N025 M01/M01 Q1024 RES	2022-01-24 09:20:00
	Q1024 TEMPO TL1000 2000 -	TSSN		2022-01-24 08:50:00
	025 M00/M02 Q1024 RESHSN TE	MPO TL1000 2000 -TSSN		2022-01-24 08:20:00

Data Preparation: Decoding Weather Data

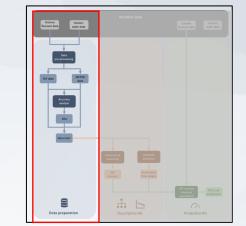
AERODROME FORECAST - TAF DECODE												
IDENTIFICATION GROUPS	FORECAST VISIBILITY VISIBILITY	FORECAST SIGNIFICANT WEATHER FORECAST	FORECAST CLOUD AMOUNT	CAVOK		CONDITIONS	ANGES IN FORECAS S INDICATED BY:		I I——		AGREEME	-
TAF or TAF AMD or CCCC YYGGggZ NIL Y,Y,6,6,7/2,Y,6,6,2 CNL TAF COR	dddff G f _m f _m KT or MPS		AND HEIGHT ^a N _s N _s N _s h _s h _s h _s (cc)	, OK	PROBABILITY PROBC ₂ C ₂	DATE AND TIME YYGG/Y _e Y _e G _e G _e	CHANGE	DATE AND TIME YYGG/Y _e Y _e G _e G _e	(TX	YYT _F T _F /Y	MPERATUR Y _e Y _e G _F G _F Z ' _A Y _e G _F G _F Z	
Indicator of cancelled Period of validity, begin (UTC) and ending on Y Indicator of missing to Indicator of UTC Date and time of issue ICAO four-letter locatio Code names for aerod amended aerodrome if corrected aerodrome	9999 = 10 km or more Wind speed units used Maximum wind speed (gust) Indicator of Gust Mean wind speed Mean wind speed	Forecast significant weather (see table www for METAR/SPECI decode) Prevailing visibility in metres Iscaed what is a second of the second of	Cloud type - only CB (cumulonimbus) is indicated Height of base of cloud in units of 30 m (100 ft) FEW - FEW (1-2 oktas) BKN - BrokeN (5-7 oktas) OVC - OVerCast (8 oktas) Replaced of the observation	Ceiling And Visibility OK. Replaces visibility, weather and cloud if: (1) Visibility is forecast to be 10 km or more (2) No cumulonimbus cloud and no other cloud forecast below 1 500 m (5 000 ft) or below the highest minimum sector attlude, whichever is greater, and (3) No significant weather forecast (see table overleaf)	the probabilities (a) an alternation elements (b) temporarion of the contained the probabilities (b) temporarion of the contained the probabilities (a) and the contained	y fluctuations eather conditions is et of conditions, thu part of the forecast,	TTYYGGgg	of another .	TX, TN Indicators of maximum and minimum forecast temperatures, respectively	YYT _F T _F Date and forecast temperature at G _F G _F Temperatures below 0°C preceded by M	~	Z Indicator of UTC
	f _m f _m = 200 KMH (100 KT, 50 MPS)	NSW WIII S	visibility is available by: VVh _s h _s h _s		YYGGgg is the	date and time in ho	where FM is the abbreviation burs and minutes UTC. All the by conditions indicated after the properties of the burners of the burners of the properties of the properties of the properties of the properties of properties of properties of properties of properties of properties of properties	forecast conditions				
	or more	II Significant Veather	Vertical visibility in units of 30 m (100 ft) Indicator of Vertical Visibility	sector altitude, which	ever is greater, and (below highest minimum egional eir navigation agreement.	For WM	Abbr	WORLD METEC		
	1 50 minir great	00 m (5 000 ft) o mum sector altii ater, is forecast a ropriate by:	o CB and no cloud below or below the highest tude, whichever is and CAVOK is not NSC					For details of codes, see WMO Manual on Codes (WIMO-No. 306)	eviated decode of TAF	WORLD METEOROLOGICAL ORGANIZATION Weather • Climate • Water		





WMO decoding instructions
+
Local decoding practices

Data Preparation: Defining accuracy KPIs





Event	Event observed			
forecast	Yes	Yes No		
Yes	а	b	a + b	
No	С	d	c + d	
Marginal total	a + c	b + d	a + b + c + d =n	



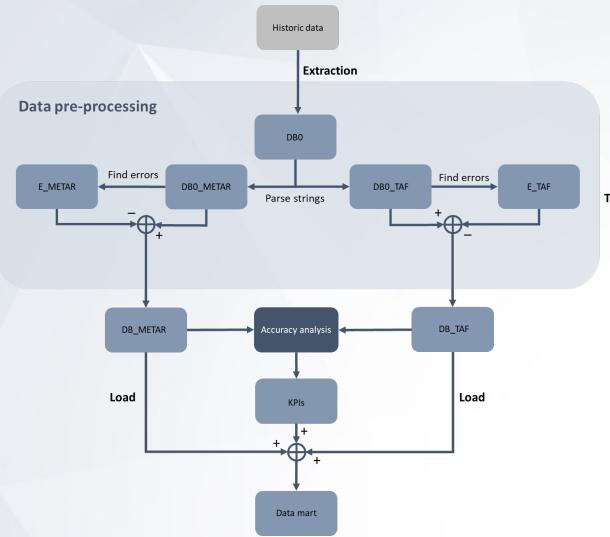
Contingency matrixes for binary parameters, which can be generalized for multi-variate parameters.

KPI	Acronym	Analytical expression
Frequency Bias Index	FBI	$FBI = \frac{a+b}{a+c} \tag{1}$
Proportion Correct	PC	$PC = \frac{a+d}{a+b+c+d} \tag{2}$
Critical Success Index	CSI	$CSI = \frac{a}{a+b+c} \tag{3}$
Probability Of Detection	POD	$POD = \frac{a}{a+c} \tag{4}$
False Alarm Ratio	FAR	$FAR = \frac{b}{a+b} \tag{5}$

Key Performance Indicators (KPIs) can be calculated accordingly.

Data Preparation: Developing the Data Mart

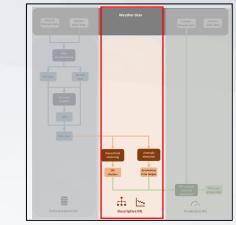




Transformation



Descriptive ML: Clustering similar forecasts (TAFs)





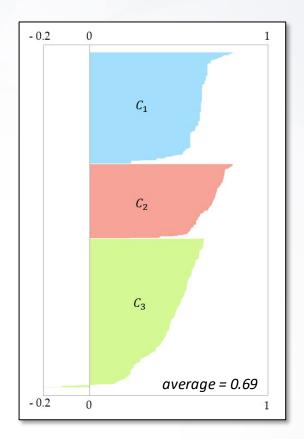
Hierarchical Clustering to spot TAFs characterized by "common" aspects

The hierarchy dendogram is obtained via the cosine distance in the M-dimensional space

$$d_{o_i o_j} = 1 - \cos\left(\theta_{o_i o_j}\right) = 1 - \frac{o_i \cdot o_j}{\|o_i\| \|o_j\|} = 1 - \frac{\sum_{m=1}^{M} o_{im} o_{jm}}{\sqrt{\sum_{m=1}^{M} o_{im}^2 \cdot \sum_{m=1}^{M} o_{jm}^2}}$$

and the Ward linkage criterion (via the Lance-Williams recursive algorithm)

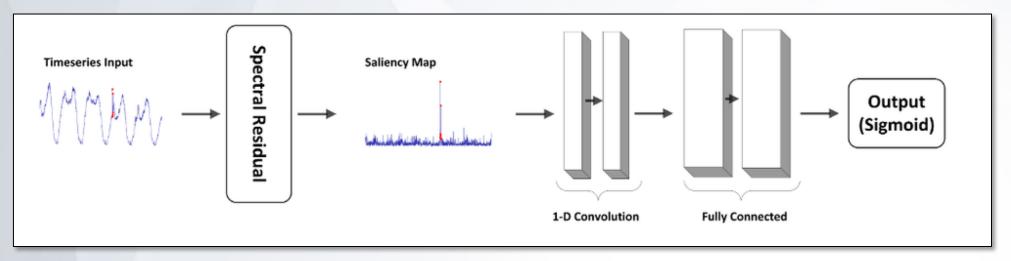
$$d_{(C_I \cup C_J)C_K} = \alpha_{C_I} d_{C_I C_K} + \alpha_{C_J} d_{C_J C_K} + \beta d_{C_I C_J} + \gamma \left| d_{C_I C_K} - d_{C_J C_K} \right|$$



Descriptive ML: Identifying anomalies



Anomaly detection to spot outliers in performance for KPIs

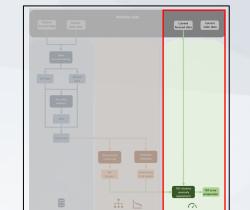


A Spectral Residual, Convolutional Neural Network is applied

$$S(x) = \left\| \mathcal{F}^{-1}(\exp(SR(f) + \sqrt{-1} \cdot P(f))) \right\|$$

$$\mathcal{A} = \{ TAF_u : u = u_{t*}, t^* \mid V_u^e \le t^* \le V_u^s \}$$

Predictive ML: Assign forecast error propensity



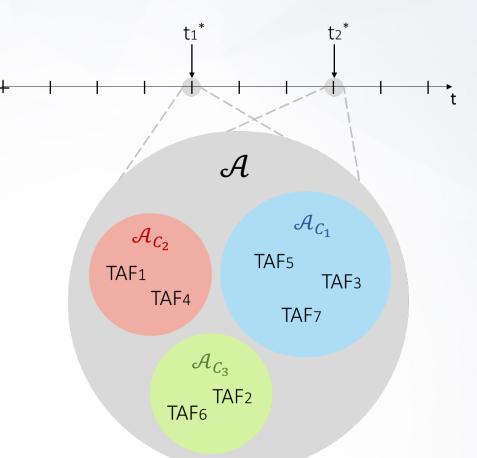
$$\mathcal{A}_{C_i} = \{ TAF_u \mid TAF_u \in \mathcal{A} \land TAF_u \text{ is classified in } C_i \}$$

$$i = 1, \dots, Nc$$

$$\eta_{C_i} = \frac{\left|\mathcal{A}_{C_i}\right|}{s_{C_i}}$$

$$i=1,\ldots,Nc$$

where $|\mathcal{A}_{C_i}|$ is the cardinality of C (i.e., number of anomalous TAFs in the i-th cluster); and s_{C_i} is the size of C_i based on the whole set of historic TAFs obtained from the clustering algorithm.



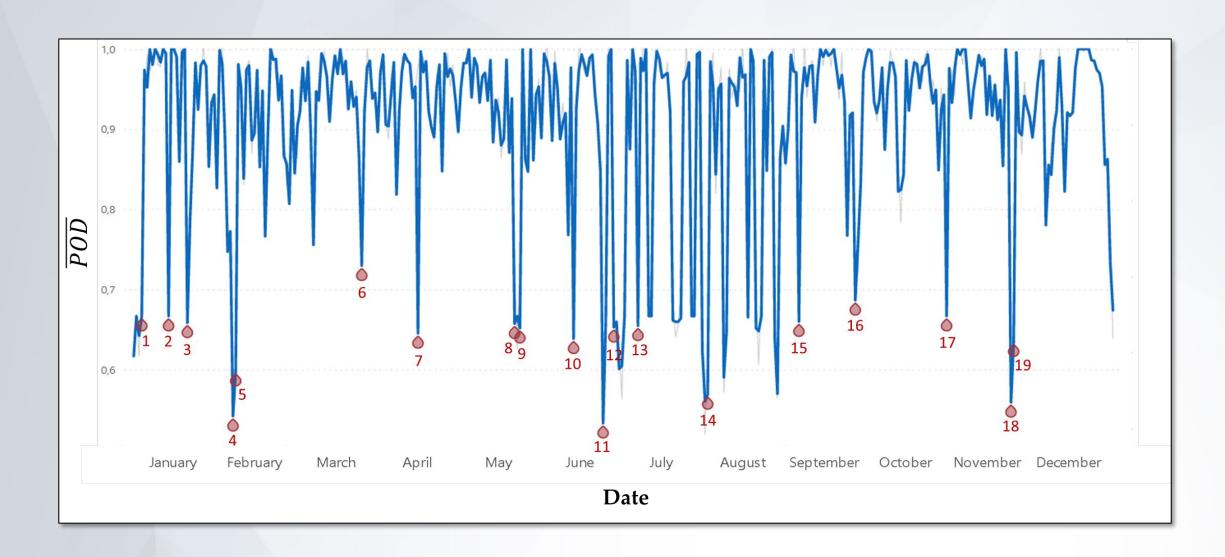
Use case: Airport X





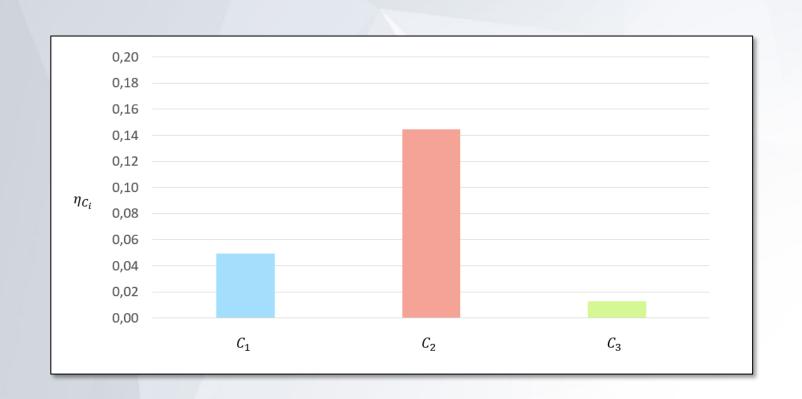
Use case: Airport X

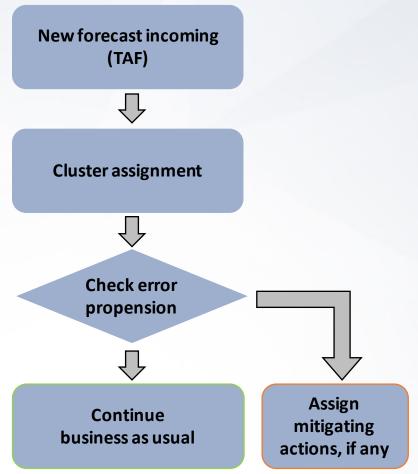


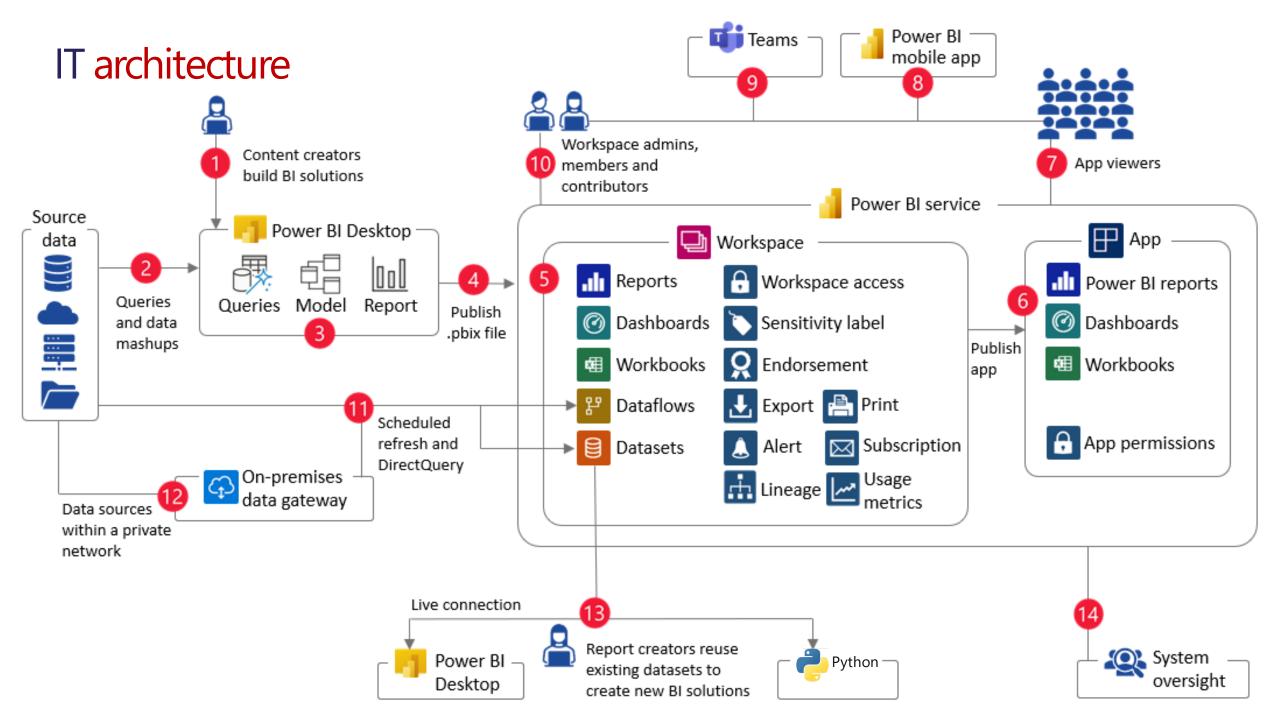


Use case: Airport X









Advantages



01

Integration in enterprise database

02

Row-level security for each data field (each user can see only their own data), using a PBI link to be provided 03

Users can navigate data live, to do self-service reporting*, export in PDF/PPT, etc.





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