Problem Statement

Predicting Crews Absence

Predicting the absence of crew before the roster planning exercise

- It is a machine learning based approach to predict the "number of crew" absent on a particular day.
- The study is for BNE, FC and Short Haul flights (73H,E90,332,73W,73C,738,73T,773)
- The result from the model would be useful to plan the roster and DOPS better and effectively utilize the standby's.

Analytics Insights from POC

- Problem Statement
- Data Description and Pre-Processing
- Data Exploration
  - Leave – Holiday Relation
  - Leave - Age Relation
  - Leave - Experience (VA) Relation
- Prediction
  - Training dataset
  - Testing dataset and accuracy
  - January 2018, Prediction

Data Description

**BNE, FC and Short Haul Flight*

Records

Dataset	Features	Dim
Fly Duty	Fly hours	113,021
Leave	Staff num, Leave availed	5654
Crew Data	Base, Rank, DoJ, Age	1,419
Australia Holiday	Holiday	17
Yearly Calendar	2017 Calendar, Weekend	365

Operations

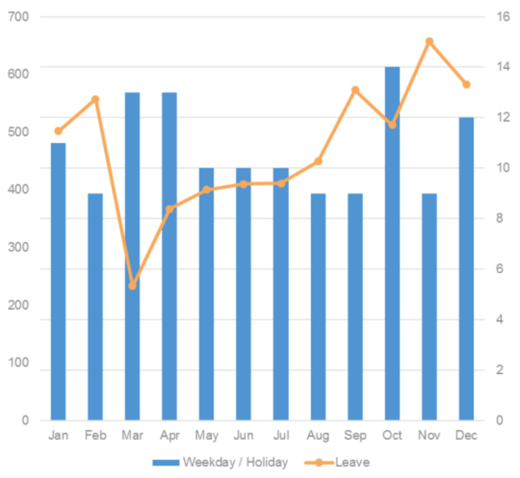
- Data is integrated and rolled up at **STAFF_NUM** and **DATE** level
- Data for year **2017** is fetched
- Only data subset of **Flight Crew** tagged with **Brisbane** for **Short Haul** flight is considered for study
- Later Fly duty data was dropped as it occupied most of the RAM and operations were consuming considerable amount of time

Short Haul Flights (73H,E90,332,73W,73C,738,73T,773)

Data Exploration

**BNE, FC and Short Haul Flight*

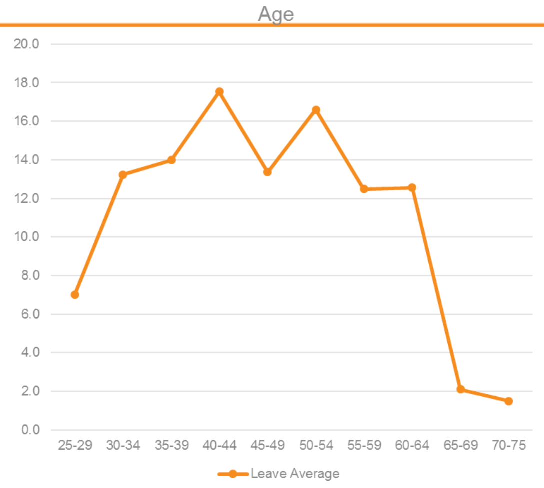
Leave Holiday Relation



Month	Leave	Weekday / Holiday
Jan	502	11
Feb	557	9
Mar	233	13
Apr	367	13
May	400	10
Jun	410	10
Jul	411	10
Aug	449	9
Sep	573	9
Oct	512	14
Nov	657	9
Dec	583	12

- Leaves are reduced with more number of holidays

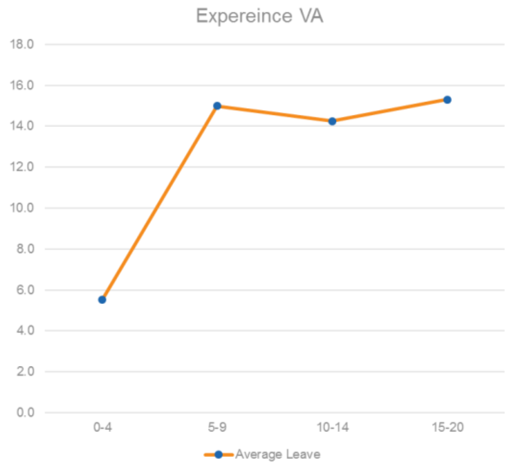
Leave Age Relation



Age Bucket	CPT	FO	RFO
25-29	0	7	7
30-34	21	14	0
35-39	19	14	8
40-44	18	18	12
45-49	14	13	-
50-54	18	10	-
55-59	12	14	-
60-64	11	16	-
65-69	2	4	-

- With Age the propensity to take leaves is going higher.
- Only limited super senior do not avail leaves.

Leave Experience Relation



Experience Bucket	CPT	FO	RFO
0-4	-	6	7
5-9	6	16	3
10-14	15	13	-
15-20	15	18	-

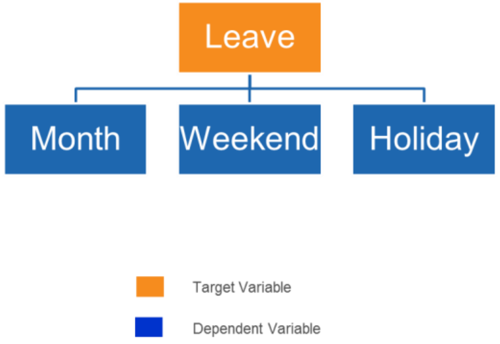
- More experience(VA) staff tend to take more leaves
- FO tends to take more leaves than CPT

Short Haul Flights (73H,E90,332,73W,73C,738,73T,773)

Predictions

**BNE, FC and Short Haul Flight*

Training Data Set



Sample Data				
Date	Month	Weekend	Holiday	leave
1-Jan-17	1	1	0	10
2-Jan-17	1	0	1	11
3-Jan-17	1	0	0	11
:	:	:	:	:
31-Oct-17	10	0	1	19

- Model is trained on first 18 months of data (January 2016 – June 30, 2017
- Few significant variables (Age and Experience) from analysis are left since most of them require staff level study with more resources of hardware and time

Testing Data and Accuracy

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{\hat{y}_i}\right) * 100$$

y_i $\quad$ $Actual\ Outcome$

- Model is created with 89% accuracy or standard deviation of 3
- Accuracy to improve with:
  - More years of data (2015 and 2016)
  - More features like Fly hours, Weather, Age and Experience
  - Crew level study and rolling up to day level

Sample Data					
Date	Month	Weekend	Holiday	leave	**Prediction**
1-Nov-17	11	0	0	18	**18**
2-Nov-17	11	0	0	18	**18**
3-Nov-17	11	0	0	21	**19**
:	:	:	:	:	**:**
31-Dec-17	12	1	0	12	**15**

- Model is tested on last 6 months of data (July 2017 – December 2017)

Short Haul Flights (73H,E90,332,73W,73C,738,73T,773)

January 2018, Prediction with 89% accuracy

*BNE, FC and Short Haul Flight

CHANGE FOR GROWTH
Travel • Insurance • Asset & Wealth Management

Total Crew 1011

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
	01 20 26	02 20 24	03 19 25	04 19 23	05 19 22	06 19 20
07 19 20	08 18 18	09 18 18	10 18 18	11 18 18	12 17 19	13 17 19
14 17 18	15 17 17	16 17 17	17 17 17	18 17 18	19 17 18	20 17 18
21 17 22	22 17 21	23 16 22	24 16 20	25 16 20	26 17 18	27 16 18
28 16 18	29 16 17	30 17 17	31 17 17			

Predicted Leaves

Actual Leaves

Short Haul Flights (73H,E90,332,73W,73C,738,73T,773)

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Use Case 1 – Crew Analytics for Predicting Absences

Predict Crew absence using historic data combined with external factors

CHANGE FOR GROWTH
Travel • Insurance • Asset & Wealth Management

Business Context

- Reduce reserve during roster planning
- Avoid underutilization of crew and thereby financial impact
- Plan optimum reserves so as to achieve OTP
- Need to predict crew absence to optimize rosters for next roster period

Solution

- Use ML to predict crew absence
- Data correlation and patterns amongst several parameters including:
  - *Pairing patterns*
  - *Leave history*
  - *Holiday List*
  - *Life events*
  - *Demographics*
  - *Weather patterns*
- Build a predictive analytics engine to predict crew absence behavior
- Open source technologies

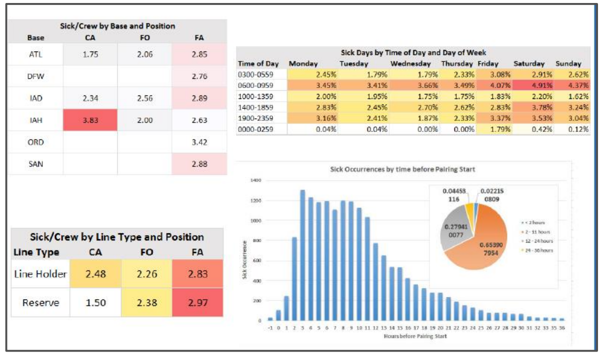
Benefits

- Optimum reserve crew planning to optimize cost and improve OTP
- Reducing unplanned management intervention that causes disruption to the schedule due to un-planned leaves

Key Business Stakeholders

- VA Network Ops (Flight and Cabin Crew)
- VA Ground Ops (Ground Crew)

Sample



Analytics Output

- Prediction analysis rolled up to fleet level to understand possible disruptions for a particular fleet for a particular route
- Prediction of Unplanned Absence Days by aircraft type / network / base / crew position

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List of Use Cases

Five Use Cases for Virgin Australia

- Use Case 1 – Crew Analytics for Predicting Absences

- Use Case 2 – Predictive Analytics for Ancillaries Sales Recommendation

- Use Case 3 – Predicting Flight Delays (more than 15 minutes)

- Use Case 4 - Forecast revenues for an airline for a season

- Use Case 5 - Forecast revenues for top 5 agents to decide on their sales incentives