Final Project: Predicting US Flight Delays using Flight Characteristics and Weather Data

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Introduction

To paraphrase a well-known idiom, 'nothing is certain but death, taxes, and delayed flights.' Flight delays are an inconvenience that almost all aviation passengers will experience at some point in their travels. Yet the burden of flight delays is not the same for all passengers. In particular, US passengers are not entitled to compensation for delays[1]. Yet, between 2013 and 2022, approximately one in every five flights from US airports was delayed by at least 15 minutes[2]. With more than 10 million scheduled passenger flights in the US each year[3], the cost to passengers of flight delays is substantial. Indeed, the *Federal Aviation Administration* estimates that flight delays in the US from 2016 to 2019 cost passengers US$62.6billion in total. Short of relying on airlines to inform them of expected delays, there is little that US passengers can do to reliably avoid flight delays. Therefore, I apply the classification methods discussed in class to determine which factors inform flight departure delays for domestic flights in the US.

Data from the *Bureau of Transportation Statistics* illustrates the prevalence of domestic flight delays. Among all US carriers, between 15–25% of departures were delayed from 2010 to 2022. Among the top US carriers[4], the proportion of delayed flights is persistently higher than average. Evidently, some US carriers exhibit fewer than average flight delays (e.g., Delta Airlines), but top US carriers tend to demonstrate more frequent flight delays than the industry as a whole.

For US passengers, the fact that top US carriers experience more frequent departure delays may be of interest in trying to avoid delays. That said, more frequent delays at top airlines do not necessarily imply more severe (i.e., costly) delays for passengers. The *Bureau of Transportation Statistics* data shows that, among all US carriers, mean departure delay lengths were between 7 and 17 minutes on average from 2010 to 2022. Unfortunately, top US carriers again appear to perform worse than the industry as a whole. Without exception, top US carriers exhibit longer-than-average delays at some point in the period.

The *Bureau of Transportation Statistics* data also highlights that the frequency of delays varies by origin airport. In line with the above, around one in every five flights from a US airport is delayed. There are clearly some airports that persistently experience more frequent delays, over 50% of all flights in some cases, and some airports that experience few or no delays.

Several factors may determine whether or not a flight is delayed and for how long. The confluence of certain factors may also make delays more likely or lengthy. Moreover, some factors are hard to observe or nearly impossible to predict. The task of anticipating delays is, therefore, extremely difficult for passengers. That said, the data above suggests that some features that are readily observable for passengers may be useful in avoiding delays. If passengers face a choice of carriers and origin airports, they may be better able to avoid costly delays by choosing those that feature less frequent and shorter delays. The aim of this analysis is to identify factors that passengers might use to anticipate delays.

[1] source:www.transportation.gov
[2] source:www.bts.gov
[3] source:www.faa.gov
[4] as measured by total number of flights serviced in 2010–2022.

Data

To identify factors that inform whether a flight is delayed on departure, I use data from the *Bureau of Transportation Statistics' Airline On-Time Performance Data*[5] for January, March, September, and December in 2016, 2017, and 2018, respectively. The flight data contains 8,777 observations on US domestic flights and 21 features, such as the flight date, origin airport, carrier, destination, distance, and other flight level characteristics. I combine this data with weather data from *Weather Underground*[6]. The weather data contains weather observations, such as average temperature, precipitation, and maximum wind speed, from corresponding airport weather stations on flight departure dates.

Compiling and Cleaning

Flight Data

I manually download *Bureau of Transportation Statistics' Airline On-Time Performance Data* for January, March, September, and December in 2016, 2017, and 2018, respectively. I import the data and compile using Pandas in Python (see corresponding Jupyter NB). The resulting dataset has 5,851,068 observations and 21 features. To make the dataset manageable, I draw a random subset (fraction=0.0015) from each month-year sample. The resulting dataset contains 8,777 observations.

Weather Data

I use web-scraping methods in Python (see corresponding Jupyter NB) to acquire historical weather data from *Weather Underground*. I use airport codes corresponding to origin airports for departures in the flight data to scrape historical weather data from airport weather stations. I acquire observations on temperatures, precipitation, sea level pressure, and max wind speed on the date of departure. The resulting dataset contains 6,190 observations.

Merged Data

I merge the flight and weather data on the date of departure and origin airport code. For the flight data, delays are identified as any flight departing more than 15 minutes late: `DepDel15=1` if delayed and `DepDel15=0` otherwise. Delays measured in minutes are given by `DepDelay`. Since the supervised learning methods I utilise rely on the assumption that **target variables** do not have missing values, I drop observations if both `DepDel15` and `DepDelay` are missing because such observations contain no useful information for the analysis.

Since I am interested in predicting delays and delay lengths using flight characteristics and weather observations, I consider the proportion of missing values for these predictor variables. I find that there are no missing observations in the flight data. However, around 70% of observations have missing values for `Day.Average.Temp`, `High.Temp`, `Low.Temp`, `Max.Wind.Speed`, and `Sea.Level.Pressure` (see Jupyter NB). Moreover, around 90% of observations have missing values for `Precipitation`. Dropping observations missing weather data is costly in terms of observations. Yet, the weather data is of interest in prediction and is likely independent of many flight characteristics. I choose to omit observations that have missing values for `Day.Average.Temp`, `High.Temp`, `Low.Temp`, `Max.Wind.Speed`, and `Sea.Level.Pressure`.

Further omitting observations that have missing values for precipitation may be discarding useful information: the correlation between `DepDel15` and `Precipitation` (0.059) and between `DepDelay` and `Precipitation` (0.026) are both non-negligible, and; mean precipitation is higher for delayed departures (0.446 inches) than for non-delayed departures (0.342 inches). Since `Precipitation` is correlated with other weather observations, I choose to impute missing values for `Precipitation` using k-Nearest Neighbours on weather data. I optimise parameter k by choosing $k \in (0, 100)$ to minimise the average MSE for in-sample prediction across 50 random sub-samples of complete weather data (see Jupyter NB). I impute missing values for `Precipitation` in the merged dataset using $k^* = 2$. The resulting dataset has 2,693 observations and 27 features.

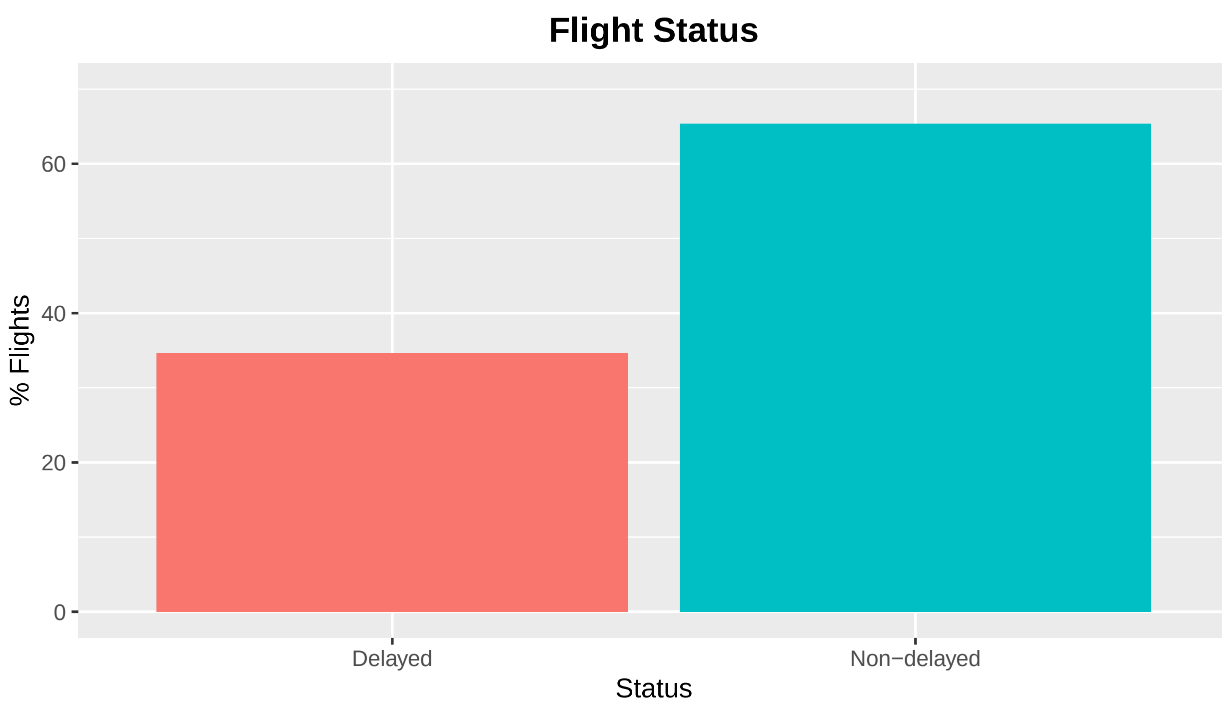
[5] www.transtats.bts.gov/
[6] www.wunderground.com

Feature Engineering

There is structure in the data that may be useful to exploit. For instance, the data already splits flight dates into `Month`, `DayofMonth`, and `DayofWeek`, which may be relevant in predicting flight delays if, for example, weekend flights are more prone to delays. In a similar vein, I re-code `DepTimeBlk`, which gives the astronomical time interval in which a departure is scheduled, as a factor variable to be used in prediction. I likewise re-code `ArrTimeBlk`. The variables `CRSDepTime` and `CRSArrTime` give the scheduled departure and arrival times of a flight in astronomical time. I find the difference in minutes between scheduled departure and arrival times to categorise scheduled flight lengths by hour in `SchFlTm`. The variable `Distance` gives the flight distance in miles, I categorise flights by distance in `DistGr` in intervals of 500 miles. I assign `InSt=1` if a flight is within state and `InSt=0` otherwise using `OriginStateName` and `DestStateName`. Finally, I use a stricter definition of a departure delay than that of `DepDel15`. I assign `Delayed=1` if `DepDelay>0` and `Delayed=0` otherwise. The dataset used for the analysis contains 2,685 observations and 31 features[7].

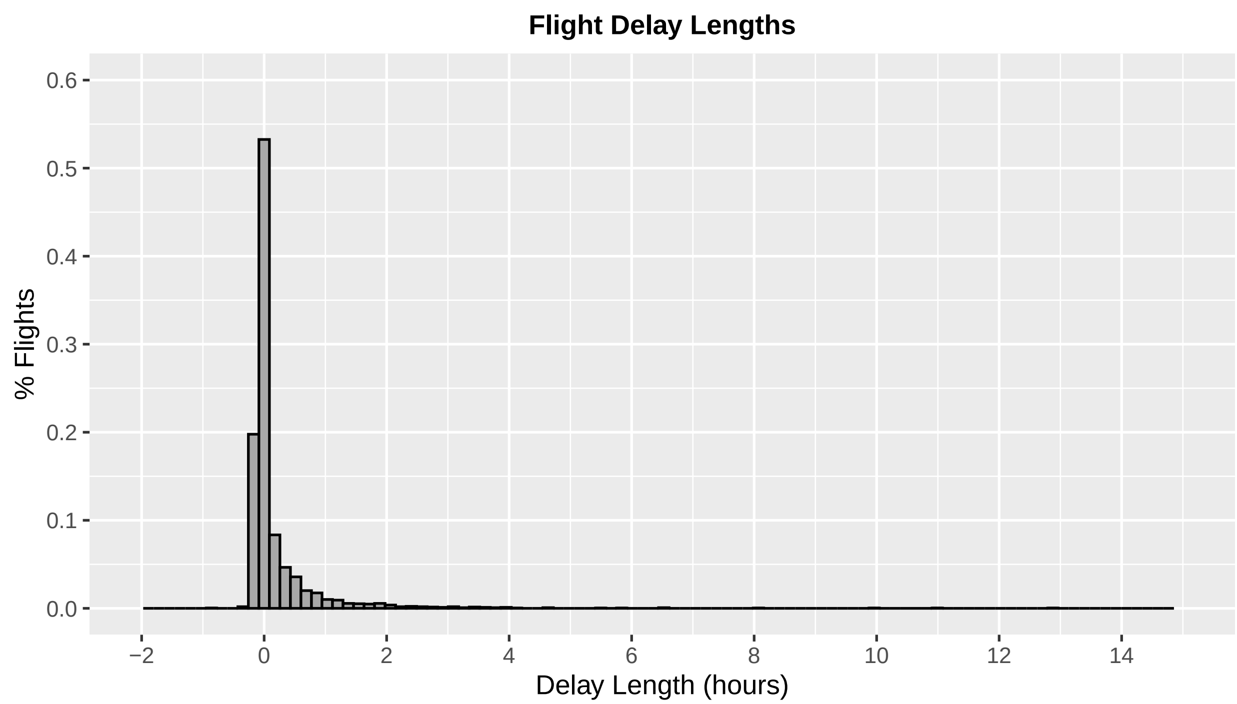
Summary

In the data, the balance of departure delays is:

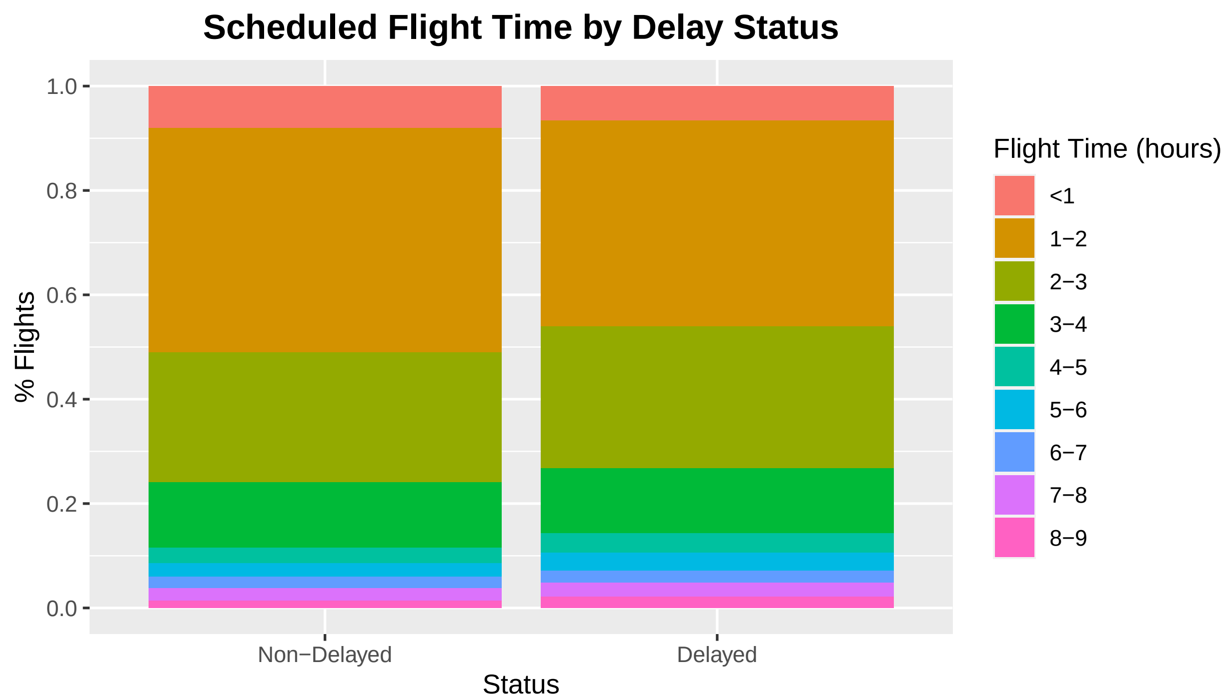


[7]Note: I remove `Flights`, which gives the number of flights per flight journey, since it is equal to one for all observations and therefore containts no useful information.

The distribution of departure delay lengths is[8]:

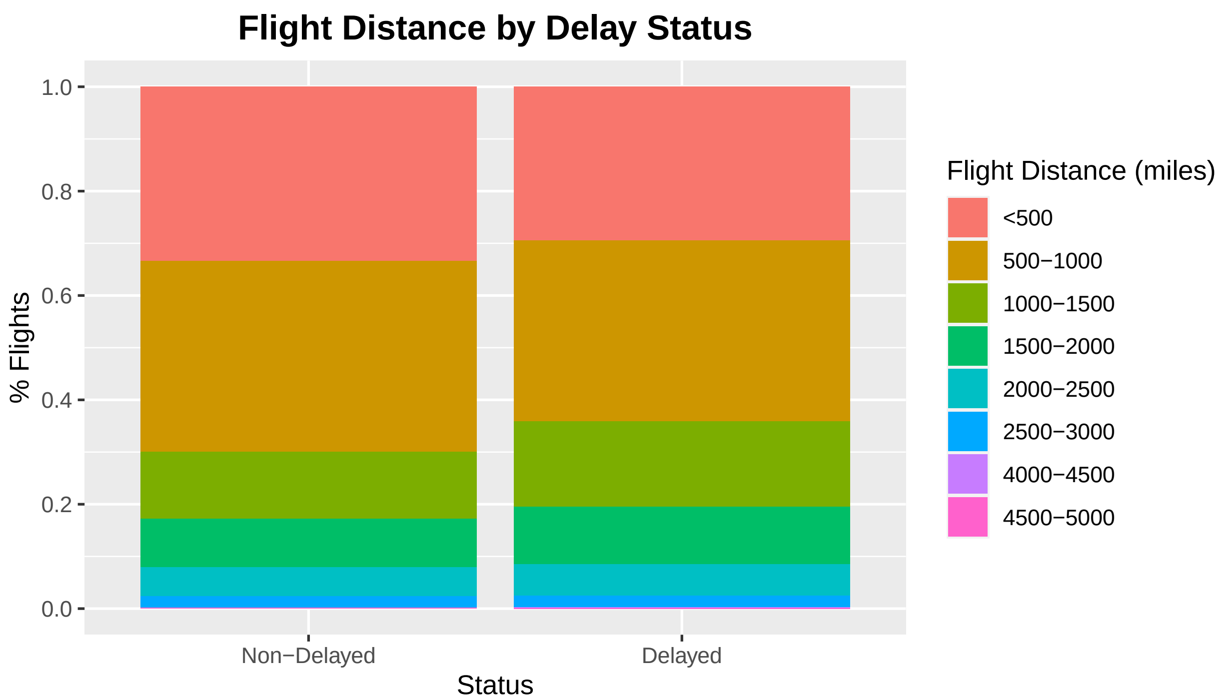


I consider the features that may be useful in distinguishing between delayed and non-delayed flights. Delayed flights tend to have longer scheduled flight times:

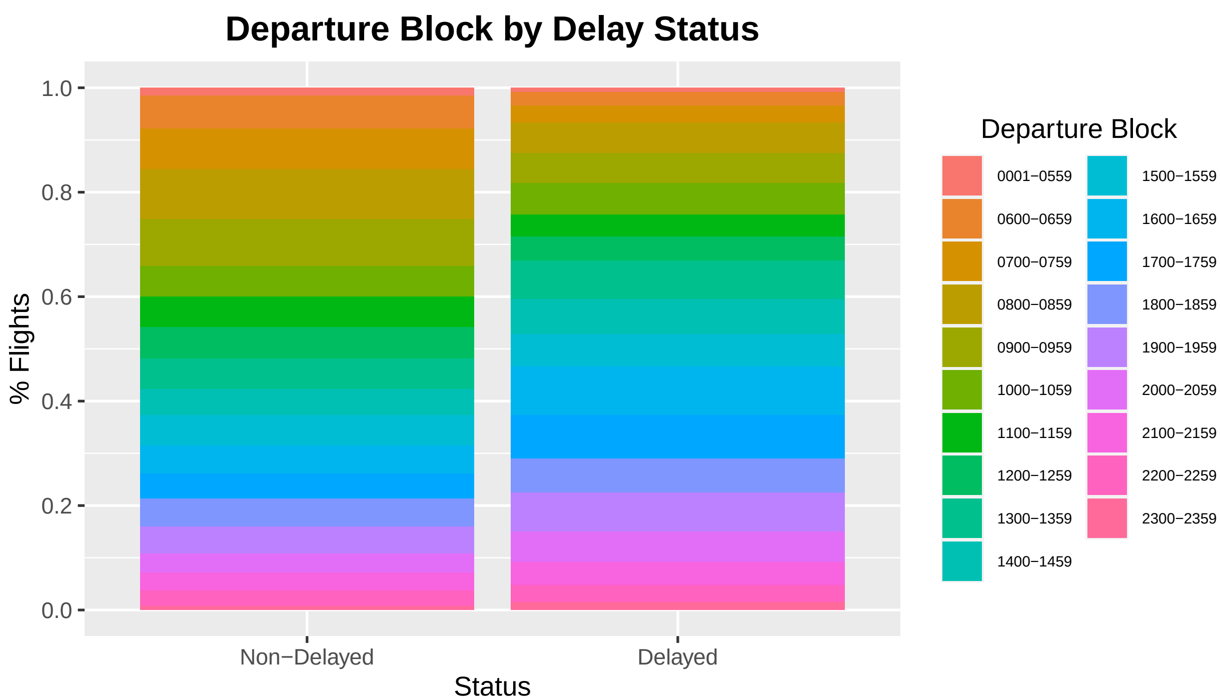


[8]Early departures have negative delay lengths.

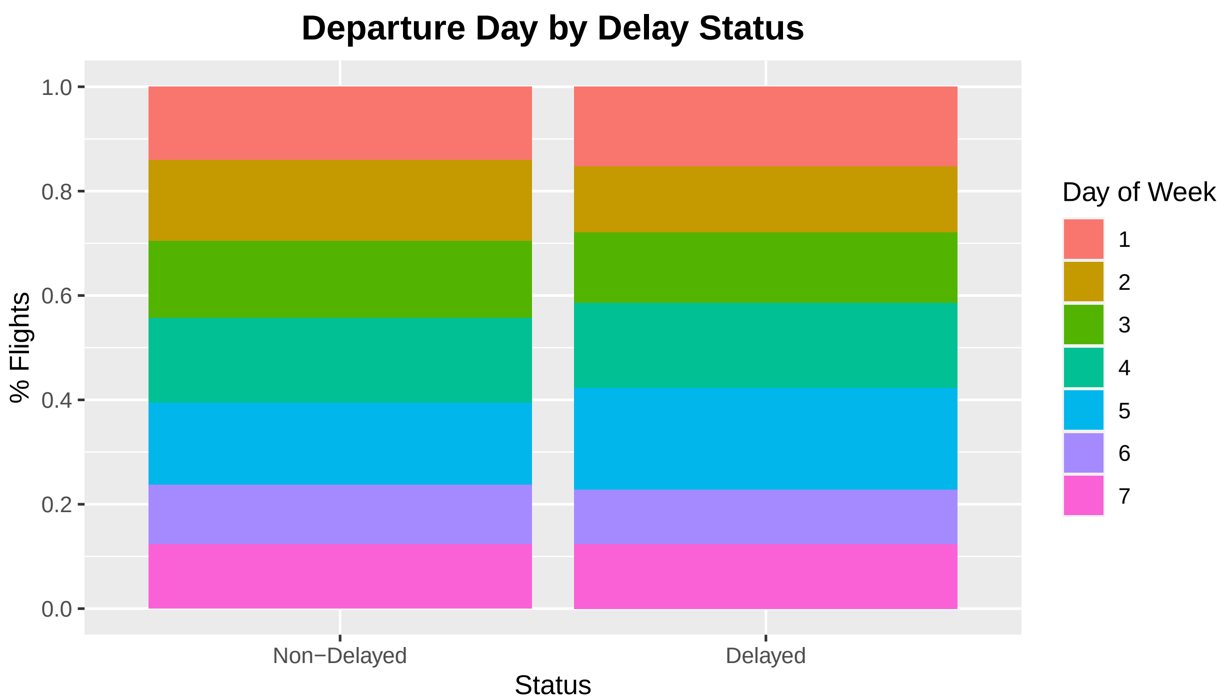
Accordingly, delayed flights tend to have greater flight distances:



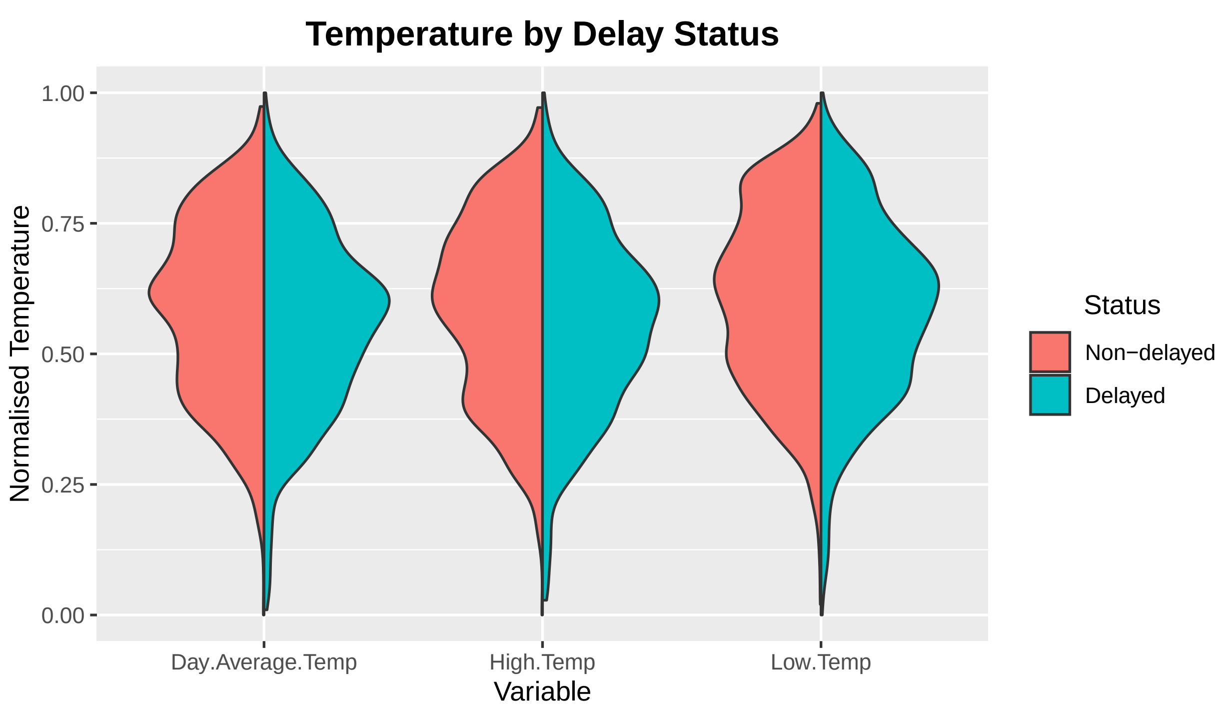
Delayed flights tend to be scheduled to depart at later in the day:



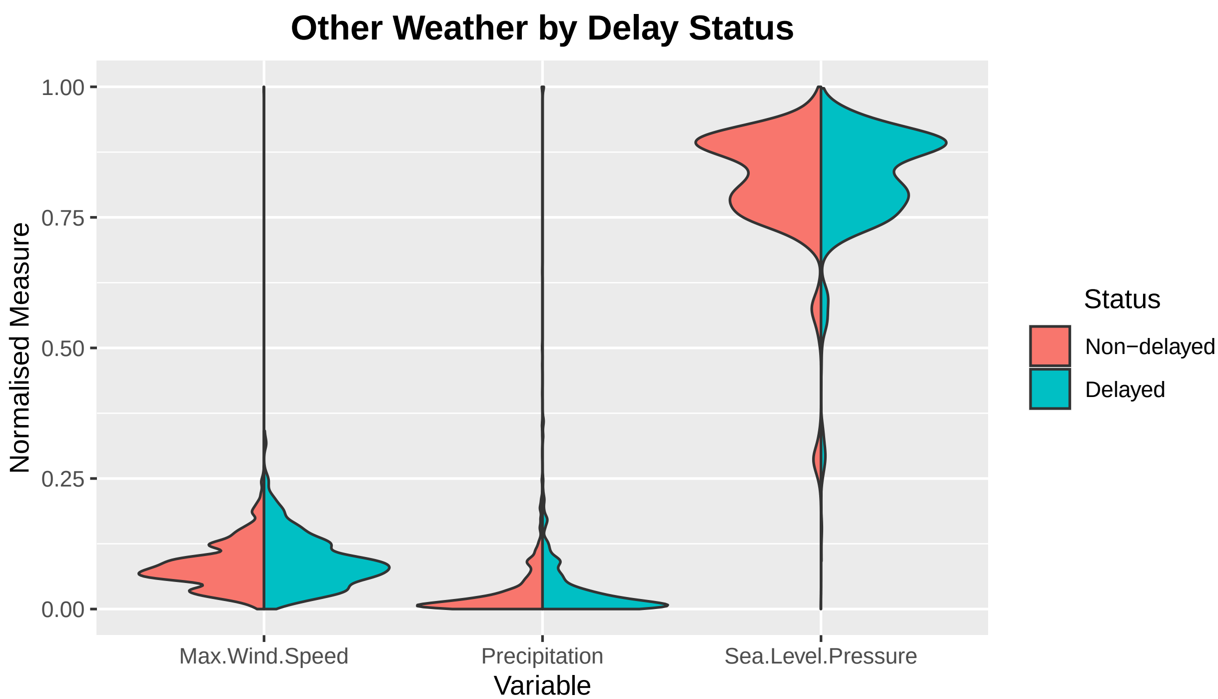
Delayed flights also tend to be scheduled to depart at later in the week (i.e., Thursday and Friday):



Flight delays appear to coincide somewhat more frequently with colder weather:



Flight delays appear to coincide somewhat more frequently with more adverse weather[9]:



Methodology and Results

Conclusion

Happy flying.

[9]note: the upper tails for `Max.Wind.Speed` and `Precipitation` belong to the distributions for delayed flights.