In [1]:
```
# Basic Libraries
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt # we only need pyplot
from plotnine import *
sb.set() # set the default Seaborn style for graphics
```

Dataset

In [2]:
```
# read data
flight_train_data=pd.read_csv('train.csv')
flight_test_data=pd.read_csv('test.csv')
```

In [3]:
```
print("Dimensions: ")
print('Train: ',flight_train_data.shape )
print('Test: ',flight_test_data.shape )
```

```
Dimensions: 
Train:  (100000, 9)
Test:  (100000, 8)
```

In [4]:
```
# combine train n test
data=pd.concat([flight_train_data,flight_test_data],axis=0,sort=False).reset_index()
# drop index columns
data=data.drop(['index'],axis=1)
```

In [5]:
```
data.head()
```

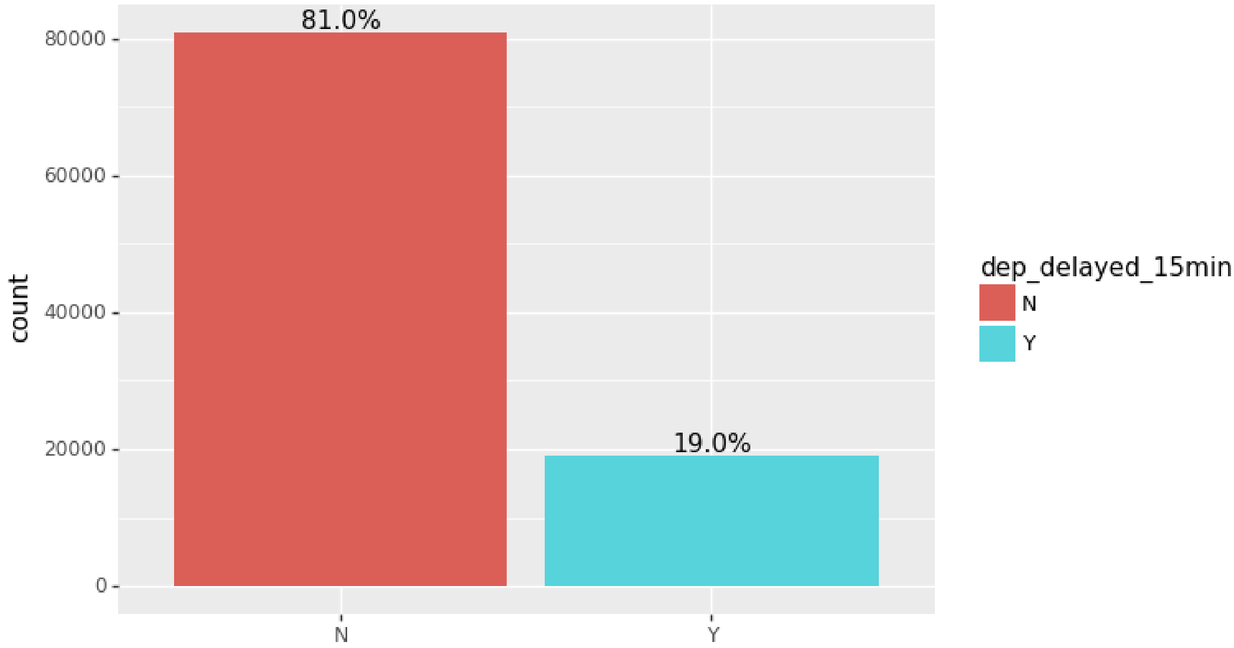
Out[5]:

	Month	DayofMonth	DayOfWeek	DepTime	UniqueCarrier	Origin	Dest	Distance	dep_delayed_15min
0	c-8	c-21	c-7	1934	AA	ATL	DFW	732	N
1	c-4	c-20	c-3	1548	US	PIT	MCO	834	N
2	c-9	c-2	c-5	1422	XE	RDU	CLE	416	N
3	c-11	c-25	c-6	1015	OO	DEN	MEM	872	N
4	c-10	c-7	c-6	1828	WN	MDW	OMA	423	Y

- Observation:
  - train and tests are split 50-50
  - train set has one additional response column as expected

Response: dep_delayed_15min

In [6]:
```
# count plot of response
ggplot(flight_train_data,aes(x='dep_delayed_15min',fill='dep_delayed_15min'))+geom_bar(
    aes(label='stat(prop)*100', group=1),
     stat='count',
     nudge_y=0.125,
     va='bottom',
     format_string='{:.1f}%'
 )
```



- Observation:
  - there is a class imbalance, only 19% of flights are delayed 15 minutes
- Action:
  - Stratified Kfold or SMOTE could be used later on to mitigate

Data exploration

check NAs

In [7]:
```
data.isna().sum()
```

Out[7]:
```
Month                     0
DayofMonth                0
DayOfWeek                 0
DepTime                   0
UniqueCarrier             0
Origin                    0
Dest                      0
Distance                  0
dep_delayed_15min    100000
dtype: int64
```

check duplicates

In [8]:
```
data[data.duplicated()]
```

Out[8]:

Month	DayofMonth	DayOfWeek	DepTime	UniqueCarrier	Origin	Dest	Distance	dep_delayed_15min

- Observation:
  - there are no NAs(100000 NAs refer to test set)
  - and no duplicates

some cleaning

In [9]:
```
# extract only the numerics from these variable
for var in ['Month','DayofMonth','DayOfWeek']:
    data[var]=data[var].apply(lambda x: x.split('-')[1])
```

- Action:
  - 'Month','DayofMonth','DayOfWeek' have a pattern of: c-(number), so we use that to extract the numerics

visualising time-based variables

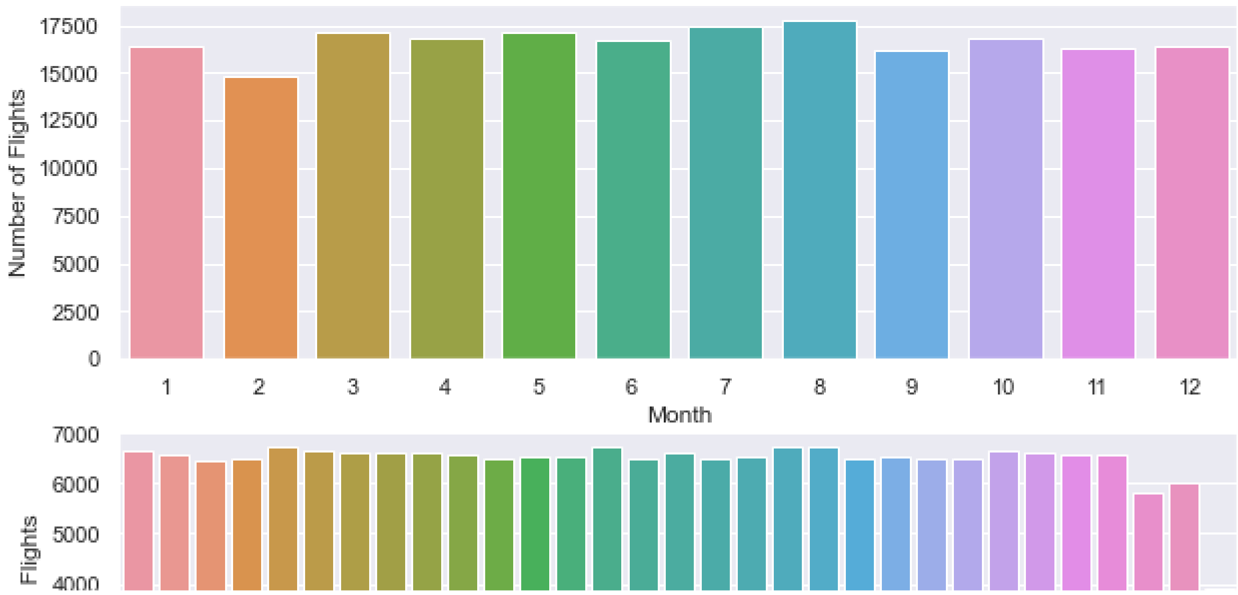
In [10]:
```
data.dtypes
```

Out[10]:
```
Month                object
DayofMonth           object
DayOfWeek            object
DepTime               int64
UniqueCarrier        object
Origin               object
Dest                 object
Distance              int64
dep_delayed_15min    object
dtype: object
```

In [11]:
```
# time-based variables to int64
for i,var in enumerate(['Month','DayofMonth','DayOfWeek']):
    data[var]=data[var].astype('int64')
```

In [12]:
```
# visualising number of flights against time-based variables
f, axes = plt.subplots(4,1 , figsize=(10, 15))
for i,var in enumerate(['Month','DayofMonth','DayOfWeek']):
    sb.countplot(data=data,x=var,ax=axes[i]).set(ylabel='Number of Flights')
sb.distplot(data['DepTime'],bins=24,kde=False,ax=axes[3]).set(ylabel='Number of Flights
```

Out[12]: `[Text(0, 0.5, 'Number of Flights')]`

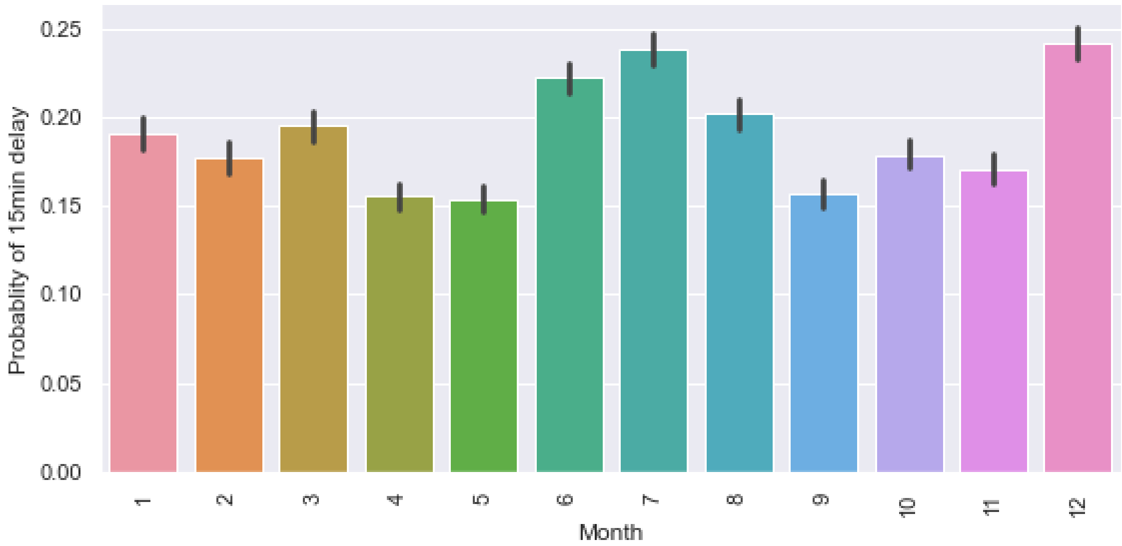


- Observation:
  - February seems to have the least flights while August the most
  - Number of flights at the end of the month also seems to be the least
  - Weekends have fewer flights than weekdays
  - most flights occur 0600-2000, fewer flights are observed at other times

In [13]:
```
# encoding response variable/delay variable (2 ways)
delay_encoding_0={'Y':1,'N':0}
delay_encoding_1=dict(zip(['Y','N'],[1,0]))
data['dep_delayed_15min_encoded']=data['dep_delayed_15min'].map(delay_encoding_1)
```

In [14]:
```
# binned departure time
bins=[]
for i in range(24):
    tuple_bin=(i*100,i*100+59)
    bins.append(tuple_bin)
interval_bins = pd.IntervalIndex.from_tuples(bins)
data['DepTime_binned']=pd.cut(data['DepTime'],interval_bins)
```

In [15]:
```
# visualise likelihood of 15 min delay agaianst the time-based variables
for i,var in enumerate(['Month','DayofMonth','DayOfWeek','DepTime_binned']):
    sb.catplot(x=var,y='dep_delayed_15min_encoded',data=data,kind='bar',height=4, aspec
```

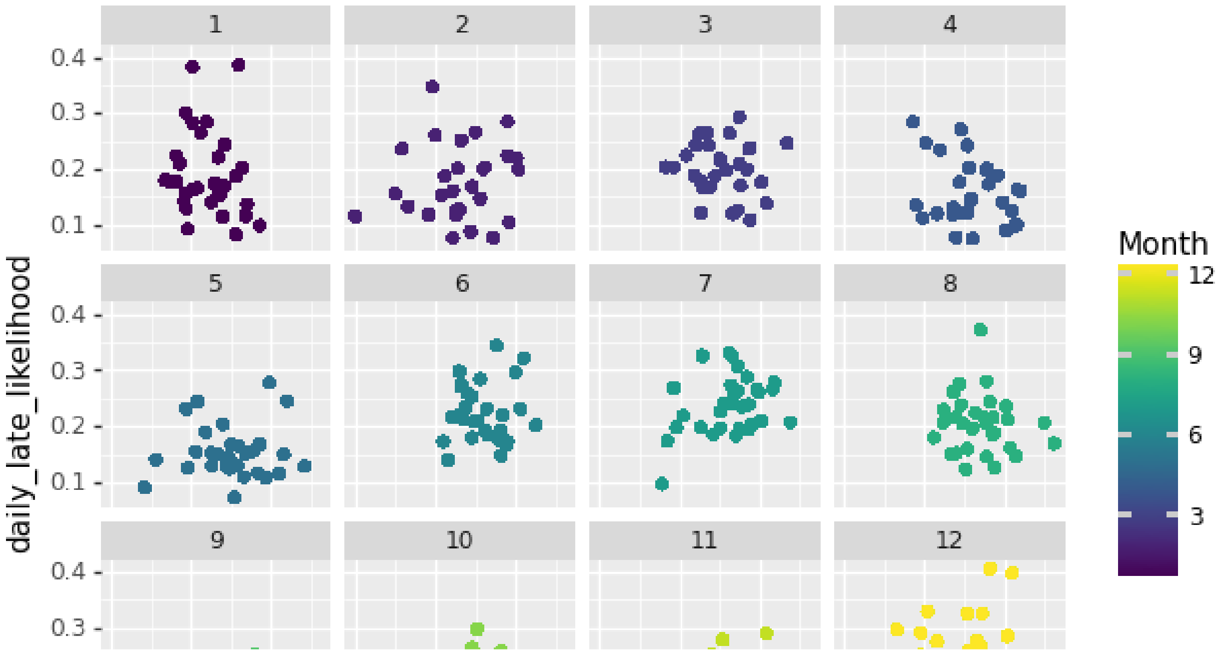


- Observation:
    - most predictive indicators:
        - mid-year
        - end of year
        - fridays
        - time of day
    - more interestingly, the likelihood of a flight delay increments starting from 0500 to 2359
    - looking at departure times, it seems like even though the number of flights from 0000 to 0359 is very low, likelihood of a late flight is the highest. same goes for flights 2100 onwards

In [16]:
```
# create a date column
data['date']=pd.to_datetime('2018/'+data.Month.astype(str)+'/'+data.DayofMonth.astype(s
```

In [17]:
```
# create likelihood of a late flight on any day of the year
daily_late_likelihood_encoding=data.groupby(['date'])['dep_delayed_15min_encoded'].agg(
data['daily_late_likelihood']=data['date'].map(daily_late_likelihood_encoding)
# create number of flights on any day of the year
daily_flight_count_encoding=data.groupby(['date'])['dep_delayed_15min_encoded'].agg(['m
data['daily_flight_count']=data['date'].map(daily_flight_count_encoding)
```

```
In [18]: ggplot(data,aes(x='daily_flight_count',y='daily_late_likelihood'))+geom_point(aes(color
```

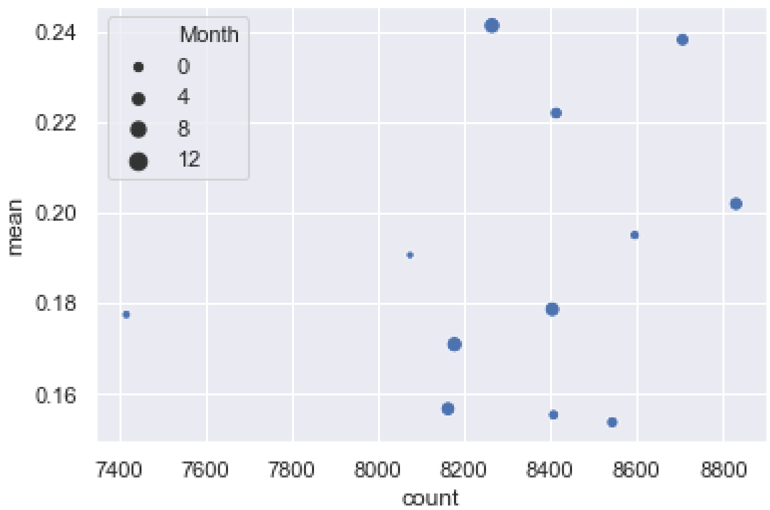


- Observation:
  - looks like there is a **poor correlation between number of fights in any given day and the likelihood of a late flight**

```
In [19]: # create likelihood of a late flight in a month
monthly_late_likelihood=data.groupby(['Month'])['dep_delayed_15min_encoded'].agg(['mean
# create number of flights in a month
monthly_flight_count=data.groupby(['Month'])['dep_delayed_15min_encoded'].agg(['mean','
```

```
In [20]: # scatterplot showing number of flights in a month against likelihood of late flight
temp_monthly_df=pd.concat([monthly_flight_count,monthly_late_likelihood],axis=1).reset_
sb.scatterplot(data=temp_monthly_df,x='count',y='mean',size=temp_monthly_df.Month)
```

```
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2729ea4fd88>
```



- Observation:
  - there are too little data points to discern anything. however, number of flights may have very little correlation w delay

visualising holidays

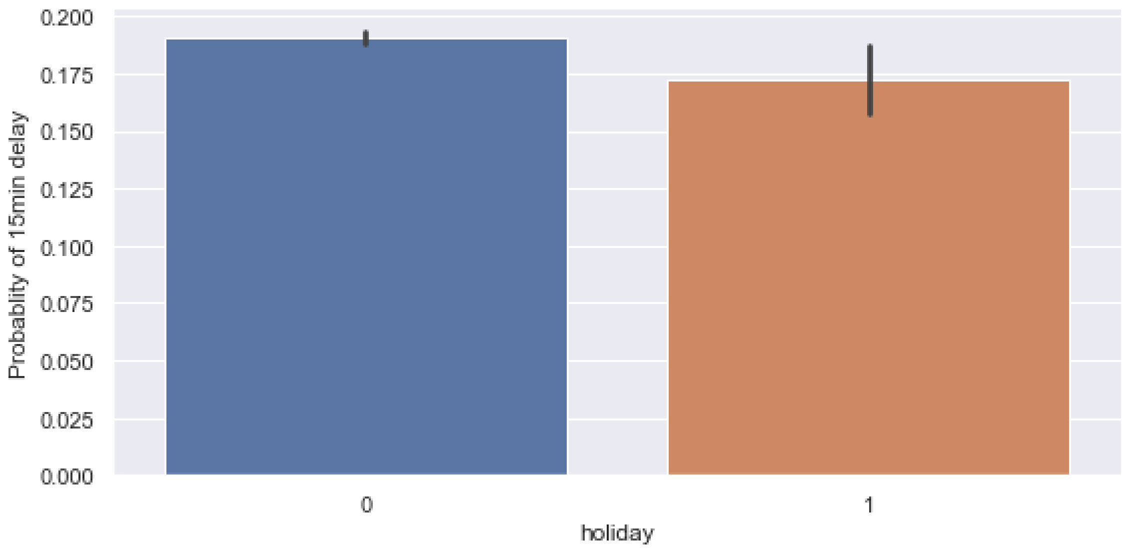
In [21]:
```
# %pip install holidays
import holidays
for date,holiday in holidays.UnitedStates(years=2018).items():
    print(date,holiday)
```

```
2018-01-01 New Year's Day
2018-01-15 Martin Luther King Jr. Day
2018-02-19 Washington's Birthday
2018-05-28 Memorial Day
2018-07-04 Independence Day
2018-09-03 Labor Day
2018-10-08 Columbus Day
2018-11-11 Veterans Day
2018-11-12 Veterans Day (Observed)
2018-11-22 Thanksgiving
2018-12-25 Christmas Day
```

In [22]:
```
# create new feature: holiday or not
holiday_dates=pd.to_datetime(list(holidays.UnitedStates(years=2018).keys()))
data=data.assign(holiday=data['date'].apply(lambda x: 1 if x in holiday_dates else 0))
```

In [23]:
```
sb.catplot(x='holiday',y='dep_delayed_15min_encoded',data=data,kind='bar',height=4, asp
```

Out[23]: <seaborn.axisgrid.FacetGrid at 0x2729ee82988>



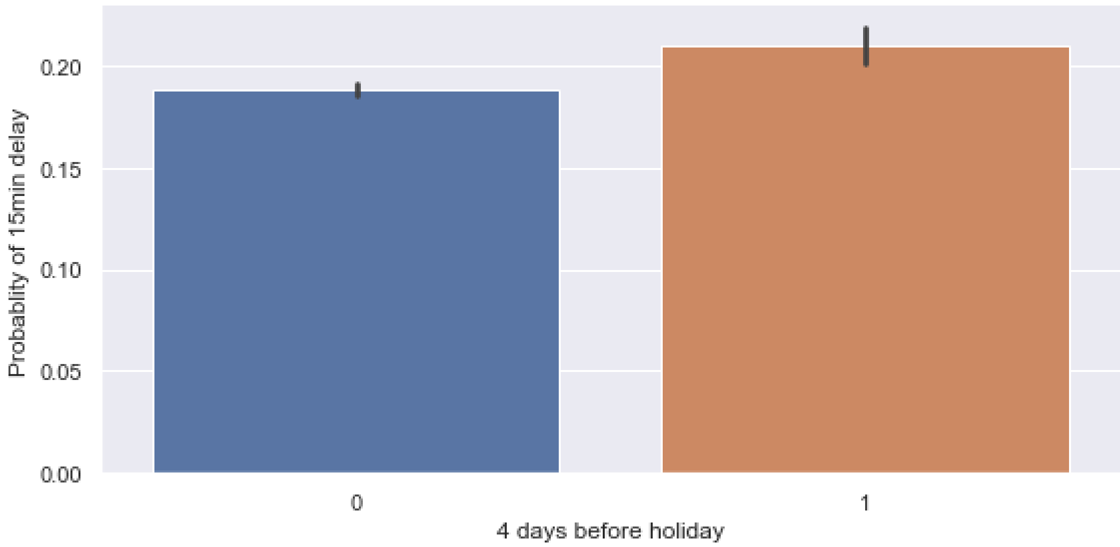
- Observation:
  - on the day of the holiday, flights are slightly less likely to be late

In [24]:
```
# get list of dates before and after holiday
import datetime
before_holiday=[]
after_holiday=[]
for date in holiday_dates:
    for i in range(1,5):
        previous_date=date-datetime.timedelta(days=i)
        coming_date=date+datetime.timedelta(days=i)
        before_holiday.append(previous_date)
        after_holiday.append(coming_date)

before_holiday=pd.to_datetime(before_holiday)
after_holiday=pd.to_datetime(after_holiday)
```

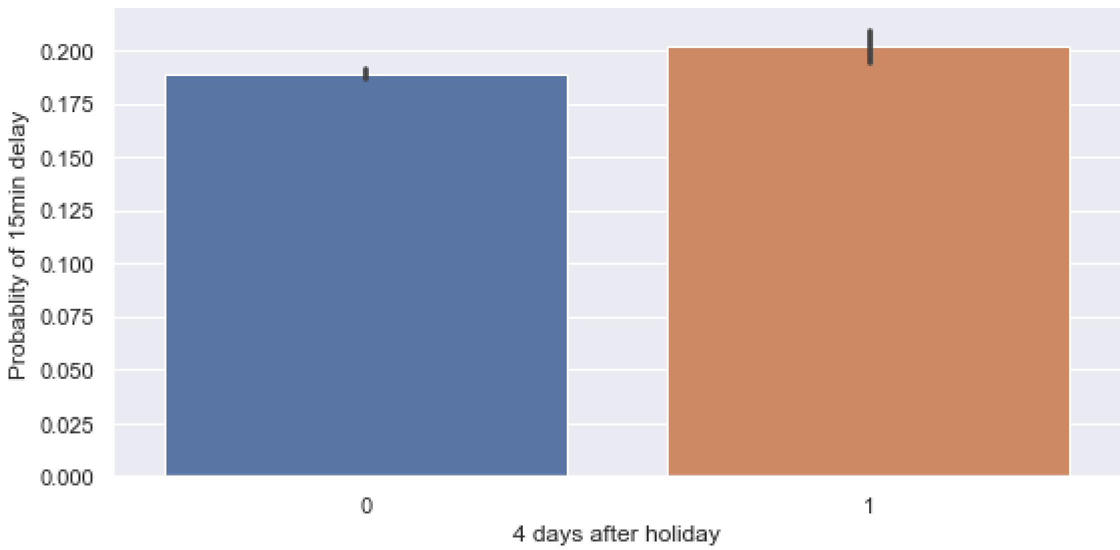
In [25]:
```
data=data.assign(before_holiday=data['date'].apply(lambda x: 1 if x in before_holiday e
sb.catplot(x='before_holiday',y='dep_delayed_15min_encoded',data=data,kind='bar',height
```

Out[25]: <seaborn.axisgrid.FacetGrid at 0x27297fb6f48>



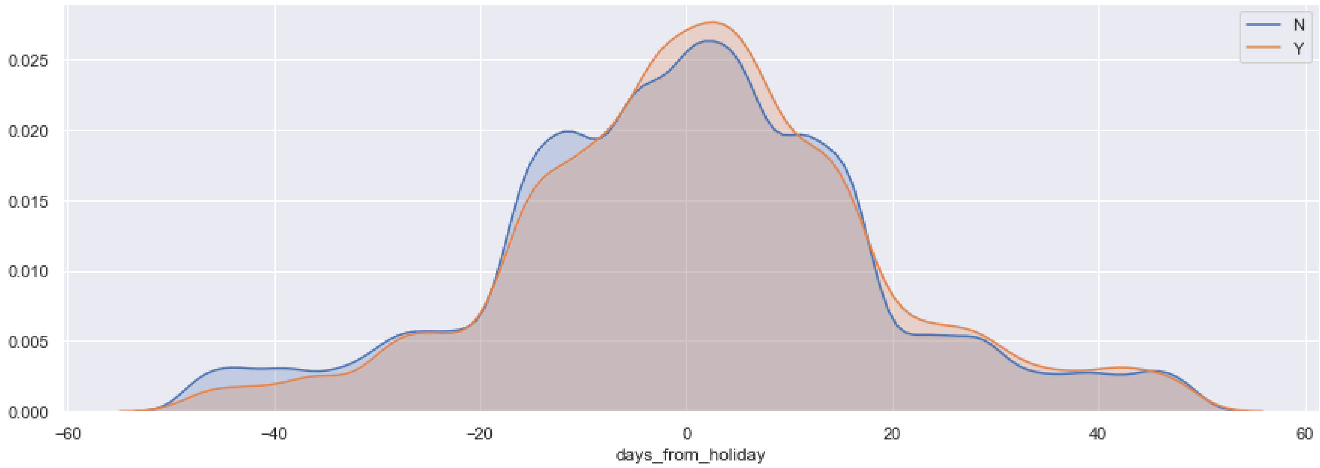
In [26]:
```
data=data.assign(after_holiday=data['date'].apply(lambda x: 1 if x in after_holiday else
sb.catplot(x='after_holiday',y='dep_delayed_15min_encoded',data=data,kind='bar',height=
```

Out[26]: <seaborn.axisgrid.FacetGrid at 0x27294e9adc8>



In [27]:
```python
# new feature: number of days from any holiday
all_dates_list=pd.to_datetime(data['date'].sort_values().unique())
days_from_holiday=[]
for date in all_dates_list:
    smallest_difference=999
    for holiday in holiday_dates:
        difference=(date-holiday).days
        if(abs(difference)<smallest_difference):
            smallest_difference=difference
    days_from_holiday.append(smallest_difference)
days_from_holiday_mapping=dict(zip(all_dates_list,days_from_holiday))
data=data.assign(days_from_holiday=data['date'].map(days_from_holiday_mapping))
```

In [28]:
```python
f, axes = plt.subplots(1,1 , figsize=(15,5))
for level in data['dep_delayed_15min'].unique():
    sb.kdeplot(data[data['dep_delayed_15min']==level]['days_from_holiday'],shade=True,l
```



- Observations:
    - flights closer to holidays are more likely to be delayed
    - flights a week before a holiday are less likely to be delayed

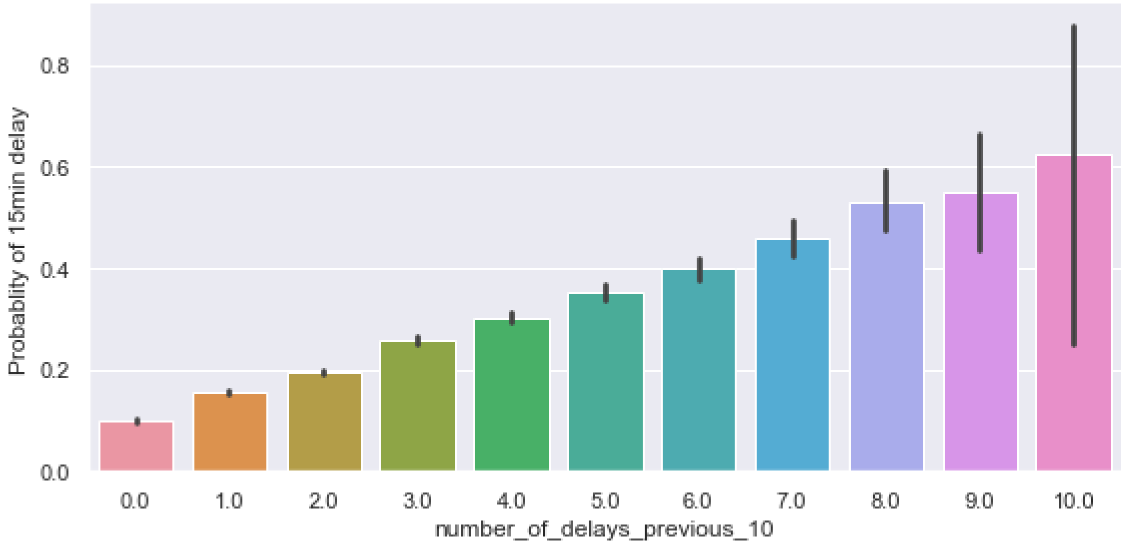
visualising effect of number of delays from the previous 10 flights

In [29]:
```python
# sort flights by date and time
testor=data.copy()
testor.dropna(subset=['dep_delayed_15min_encoded'],axis=0,inplace=True)
subset=testor.sort_values(by=['date','DepTime'])
delayed_subset=subset['dep_delayed_15min_encoded']
```

In [30]:
```python
# encode flights by their sum of flights delays out of the previous 10 flights
number_of_delays_previous_10=[]
for day in subset['date'].unique():
    daily_flight_delays=subset[subset['date']==day]['dep_delayed_15min_encoded']
    for i in range(10):
        number_of_delays_previous_10.append(None)
    for ordered_flight in range(10,len(daily_flight_delays)):
        temp=daily_flight_delays[ordered_flight-10:ordered_flight].sum()
        number_of_delays_previous_10.append(temp)
```

In [31]:
```
subset['number_of_delays_previous_10']=number_of_delays_previous_10
sb.catplot(x='number_of_delays_previous_10',y='dep_delayed_15min_encoded',data=subset,k
```

Out[31]: `<seaborn.axisgrid.FacetGrid at 0x2729ac5bd48>`



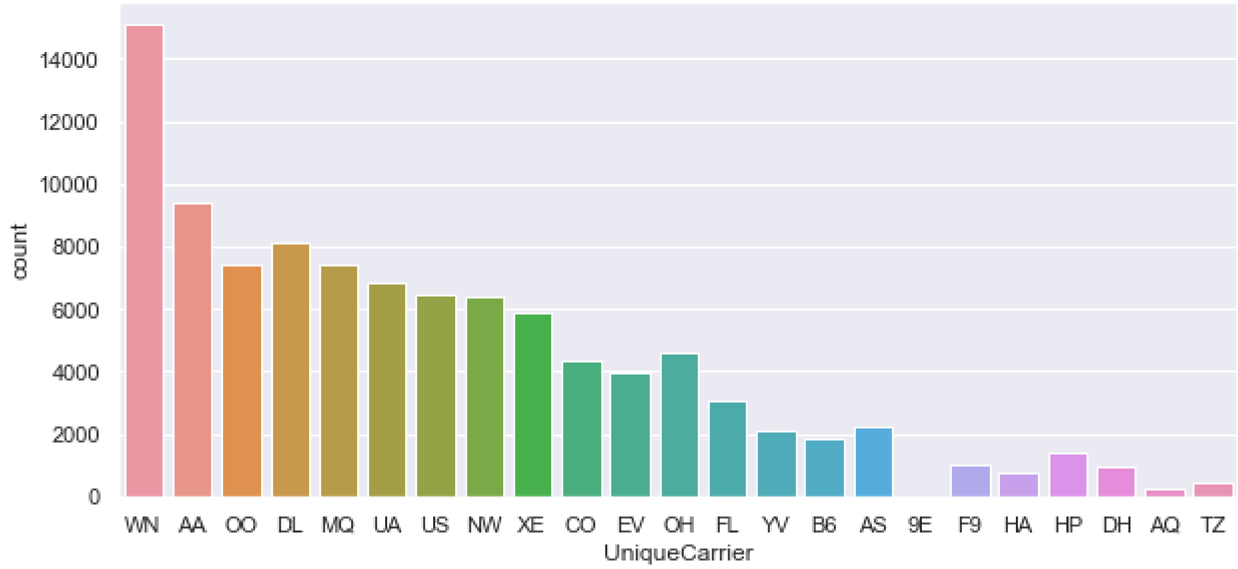
- Observation:
  - flights delays can snowball, which explains why likelihood of delays increase throughout the day

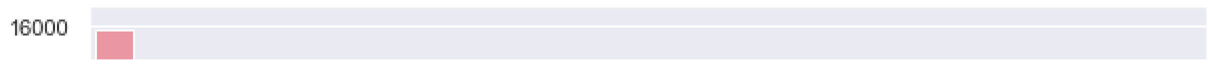
visualising UniqueCarrier

In [32]:
```
print("Unique carriers: ",data.UniqueCarrier.unique())
print("Number of unique carriers: ",len(data.UniqueCarrier.unique()))
```

```
Unique carriers:  ['AA' 'US' 'XE' 'OO' 'WN' 'NW' 'DL' 'OH' 'AS' 'UA' 'MQ' 'CO' 'EV' 'D
H'
 'YV' 'F9' 'AQ' 'TZ' 'HP' 'B6' 'FL' 'HA' '9E']
Number of unique carriers:  23
```

In [33]:
```python
# value counts of Carriers (training set followed by test set)
f, axes = plt.subplots(2,1 , figsize=(10, 10))
for i,sets in enumerate([flight_train_data,flight_test_data]):
    sb.countplot(data=sets,x='UniqueCarrier',ax=axes[i],order=list(data.UniqueCarrier.v
```

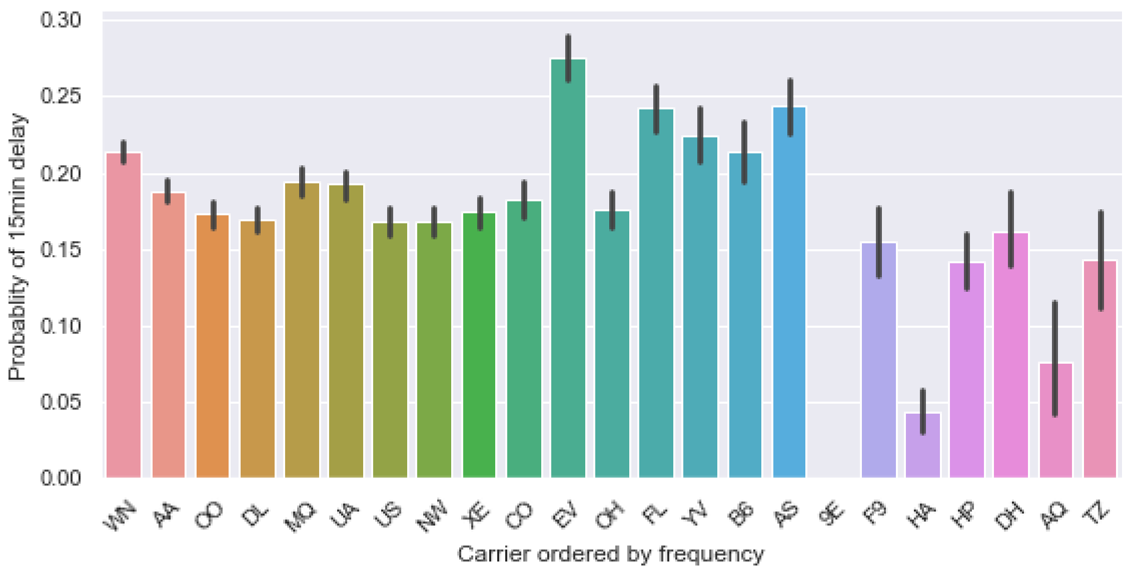




- Obseravtion:
  - **Carrier 9E is present in test set but completely missing in the training set**
  - **certain carriers present in the training set is also absent from the test set**

In [34]:
```python
sb.catplot(x='UniqueCarrier',y='dep_delayed_15min_encoded',data=data,kind='bar',height=
```

Out[34]: <seaborn.axisgrid.FacetGrid at 0x2729a4c6d48>



- Observation:
  - the above plot also orders carriers by frequency.
  - even though carriers like EV and AS are not as frequent, their likelihood of being late is much higher
  - this concludes that the **competency of carriers is also a factor** in determining whether a flight is late
    - e.g. EV carrier may not be as good (in terms of punctuality) compared to OO carrier

In [35]:

```python
# labels a categorical variable by their rank based on frequency
def labelcount_encode(X, categorical_features, ascending=False):
    print('LabelCount encoding: {}'.format(categorical_features))
    X_ = pd.DataFrame()
    for cat_feature in categorical_features:
        cat_feature_value_counts = X[cat_feature].value_counts()
        value_counts_list = cat_feature_value_counts.index.tolist()
        if ascending:
            # for ascending ordering
            value_counts_range = list(
                reversed(range(len(cat_feature_value_counts))))
        else:
            # for descending ordering
            value_counts_range = list(range(len(cat_feature_value_counts)))
        labelcount_dict = dict(zip(value_counts_list, value_counts_range))
        X_[cat_feature] = X[cat_feature].map(
            labelcount_dict)
    X_ = X_.add_suffix('_labelcount_encoded')
    if ascending:
        X_ = X_.add_suffix('_ascending')
    else:
        X_ = X_.add_suffix('_descending')
    X_ = X_.astype(np.uint32)
    return X_
```

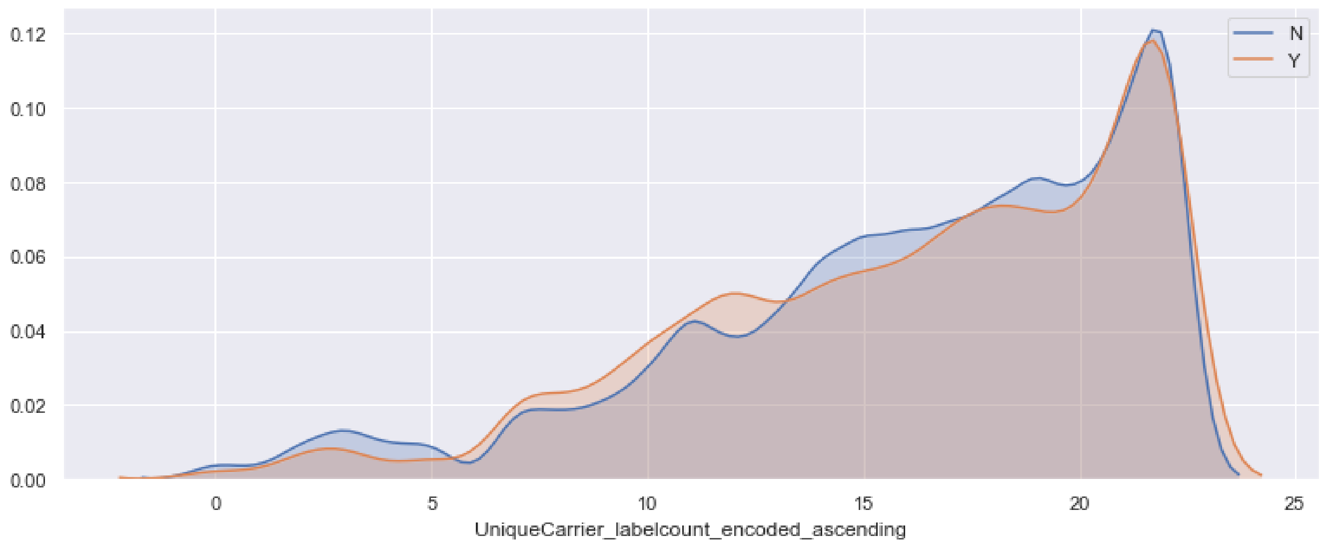
In [36]:

```python
# encode UniqueCarrier by frequency rank
data=pd.concat([data,labelcount_encode(data,['UniqueCarrier'], ascending=True)],axis=1)
```

```
LabelCount encoding: ['UniqueCarrier']
```

In [37]:

```python
f, axes = plt.subplots(1,1 , figsize=(13,5))
for level in data['dep_delayed_15min'].unique():
    sb.kdeplot(data[data['dep_delayed_15min']==level]['UniqueCarrier_labelcount_encoded_
```



- Observation:
  - most frequnt carriers are more likely to be late
  - moderately frequent carriers(rank 16-20) are less likely to be late
  - less frequent carriers(rank 6-16) are more likely to be late

Origin and Destinations

In [38]:

```
print("Number of levels: ")
for var in ['Origin','Dest']:
    print('{:<10}:{}'.format(var,len(data.Origin.unique())))
```

```
Number of levels: 
Origin    :307
Dest      :307
```

In [39]:

```
print("Value counts: ")
for var in ['Origin','Dest']:
    print(data[var].value_counts())
```

```
Value counts: 
ATL    11387
ORD     9823
DFW     8163
LAX     6434
DEN     6222
       ...  
CMX        2
ALO        2
EAU        1
VCT        1
VIS        1
Name: Origin, Length: 307, dtype: int64
ATL    11382
ORD     9877
DFW     8290
LAX     6445
DEN     6115
       ...  
```

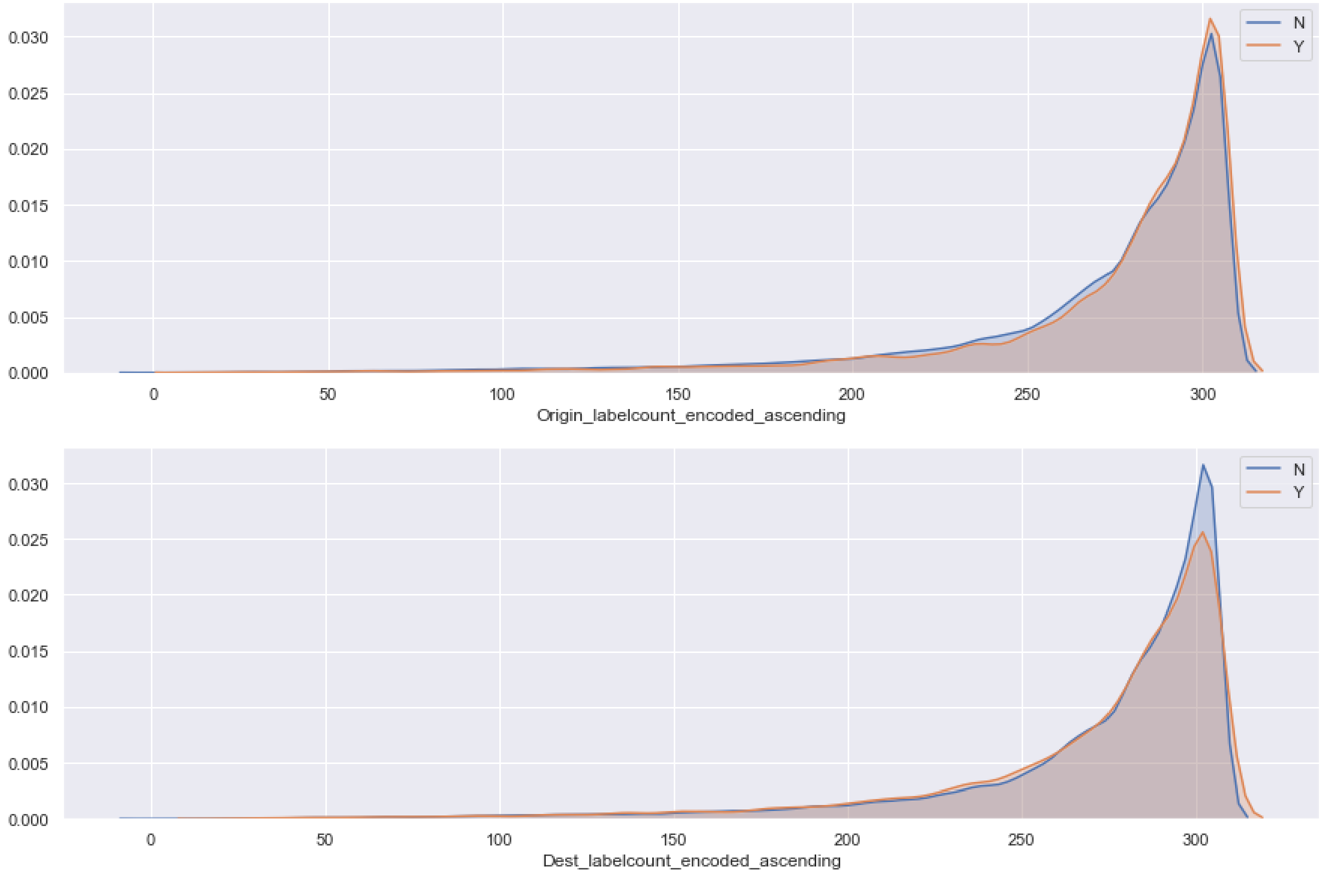
- Observation:
  - Conveniently, there is the same number of Origin and Dest airports

In [40]:

```
# encode by frequency rank
data=pd.concat([data,labelcount_encode(data,['Origin','Dest'], ascending=True)],axis=1)
```

```
LabelCount encoding: ['Origin', 'Dest']
```

In [42]:
```
f, axes = plt.subplots(2,1 , figsize=(15,10))
for level in data['dep_delayed_15min'].unique():
    sb.kdeplot(data[data['dep_delayed_15min']==level]['Origin_labelcount_encoded_ascend
for level in data['dep_delayed_15min'].unique():
    sb.kdeplot(data[data['dep_delayed_15min']==level]['Dest_labelcount_encoded_ascendin
```

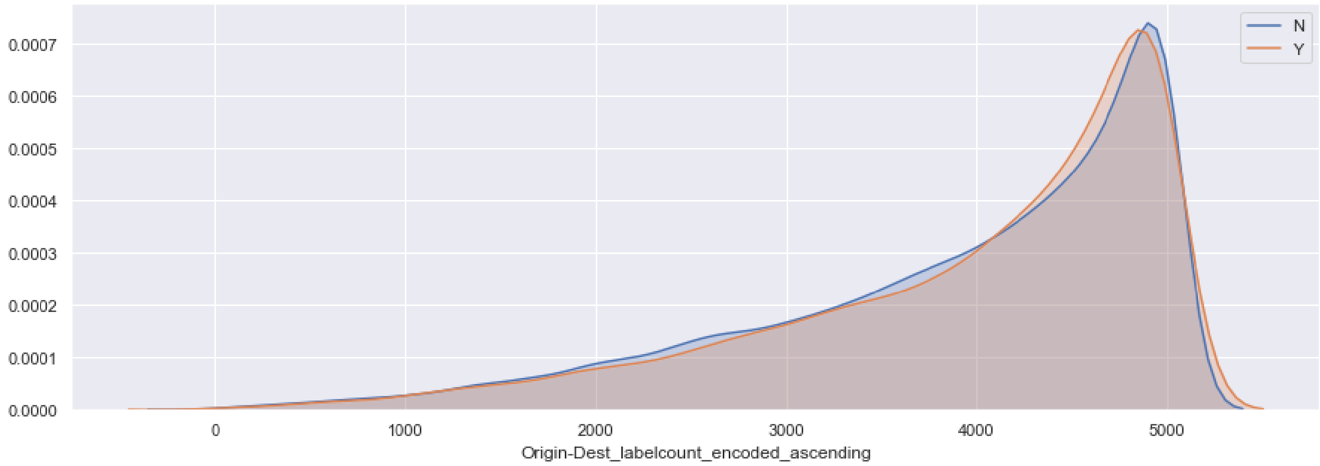


- Observation:
  - more frequent origin airports actually have a **higher likelihood of being late(larger orange area under curve)**
  - less frequent origin airports have a lower likelihood of being late(smaller orange area under curve)
  - the effects are very marginal however.
  - for dest airports around the rank of 300 in frequency have **less likelihood of being late**

In [43]:
```
# combining Origin n Dest
data['Origin-Dest']=data['Origin']+data['Dest']
# frequency encode
data=pd.concat([data,labelcount_encode(data,['Origin-Dest'], ascending=True)],axis=1)
```

```
LabelCount encoding: ['Origin-Dest']
```

In [45]:
```
f, axes = plt.subplots(1,1 , figsize=(15,5))
for level in data['dep_delayed_15min'].unique():
    sb.kdeplot(data[data['dep_delayed_15min']==level]['Origin-Dest_labelcount_encoded_a
```

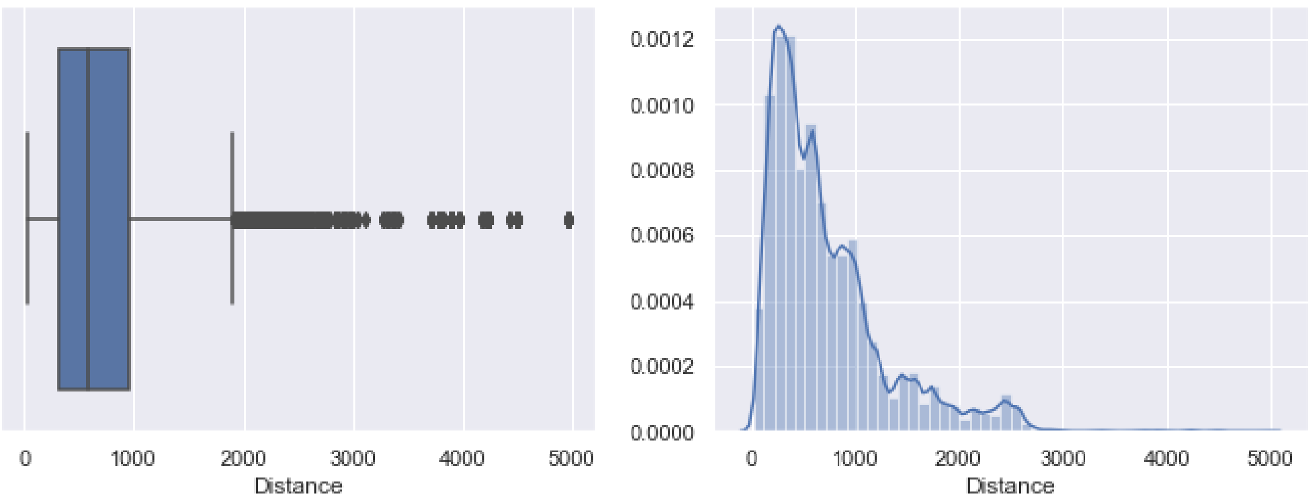


- Observation:
  - certain origin-dest pairs actually have a lower than average likelihood of being late
  - on the other hand, certain origin-dest pairs actually have a **higher than average likelihood of being late**, even though they are quite frequent occurences

distance

In [46]:
```
# uni-variate plots
f, axes = plt.subplots(1,2 , figsize=(12,4))
sb.boxplot(data.Distance,ax=axes[0])
sb.distplot(data.Distance,ax=axes[1])
```

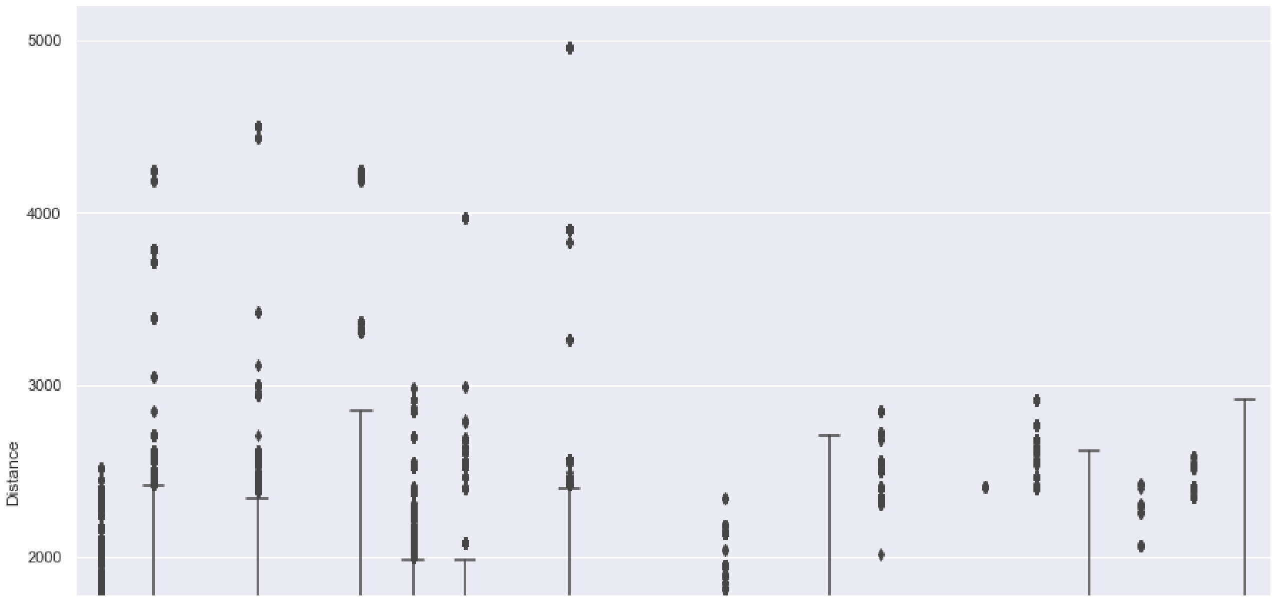
Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x2729d7f1e88>



- Observation:
  - most flights are around 250 to 1000 miles

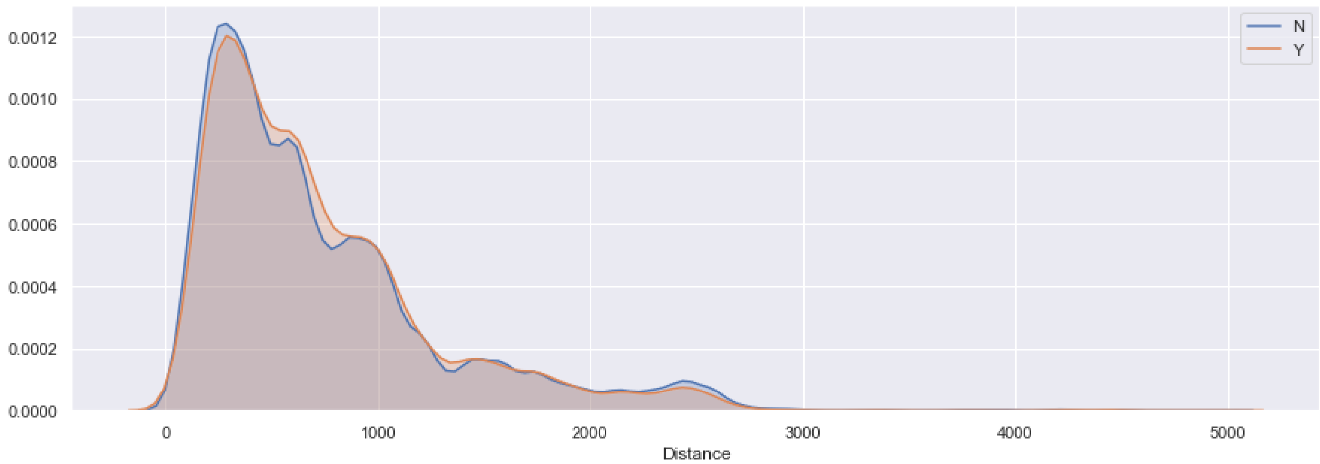
In [47]:
```
# distance against unique carriers
f, axes = plt.subplots(1,1 , figsize=(15,12))
sb.boxplot(data=data,x='UniqueCarrier',y='Distance',order=list(data.UniqueCarrier.value
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x2729d96b808>

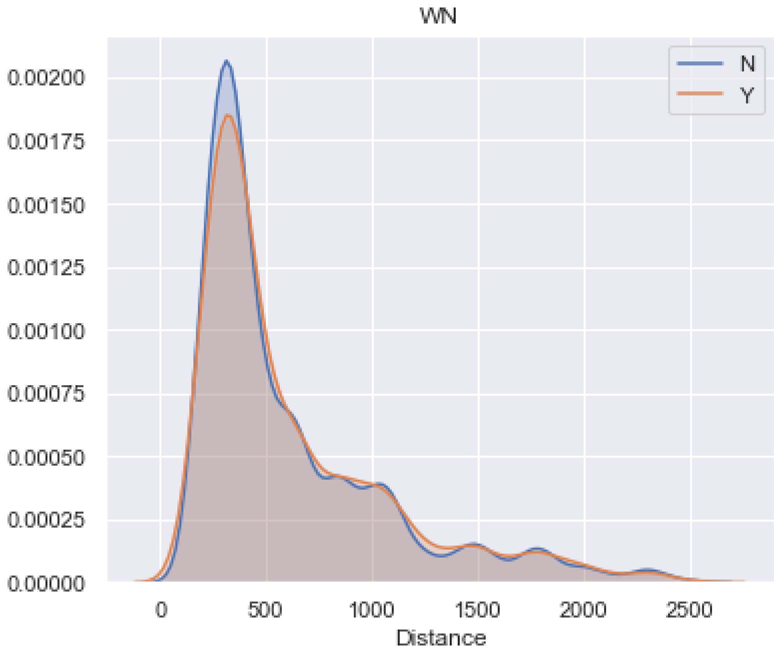


- Observation:
  - certain carriers tend to service flights that are shorter in distance like HA and AQ, which may be a reason why their lieklihood of delay is low
  - however, there are cases when this notion does not hold.
    - e.g. WN has a lower distance IQR than UA, but UA has a lower likelihood of a late flight

In [49]:
```
# KDE of flight distance segmented by the response
f, axes = plt.subplots(1,1 , figsize=(15,5))
for level in data['dep_delayed_15min'].unique():
    sb.kdeplot(data[data['dep_delayed_15min']==level]['Distance'],shade=True,label=leve
```



In [50]:
```
# these plots are also ordered by frequncy of the carrier in descending order
multiplier=len(data.UniqueCarrier.unique())
f, axes = plt.subplots(multiplier,1 , figsize=(6,6*multiplier))
for i,carrier in enumerate(list(data.UniqueCarrier.value_counts().index)):
    subset=data[data['UniqueCarrier']==carrier][['Distance','dep_delayed_15min']]
    for level in data['dep_delayed_15min'].unique():
        sb.kdeplot(subset[subset['dep_delayed_15min']==level]['Distance'],shade=True,la
```



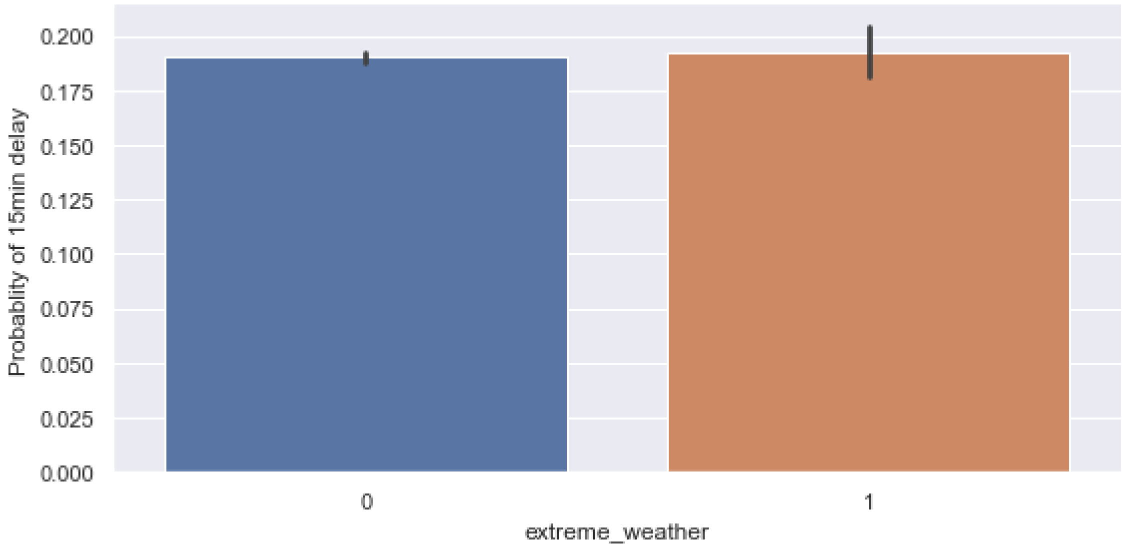
- Observation:
  - for carrier like MQ, NW and OH lower distance travels are more likely to be late(higher area under curve)
  - however, this notion does not hold for certain less frequent carriers like TZ and B6

visualising extreme weather(US)

In [51]:
```
# dates extracted from: https://www.weather.gov/mob/events
extreme_weather=pd.to_datetime(['2018-12-27','2018-12-28','2018-11-30','2018-12-01','20
                '2018-09-04','2018-09-05','2018-07-22','2018-06-28','2018-04-14','2018-
                 '2018-05-28'])
```

In [52]:
```
data=data.assign(extreme_weather=data['date'].apply(lambda x: 1 if x in extreme_weather
sb.catplot(x='extreme_weather',y='dep_delayed_15min_encoded',data=data,kind='bar',heigh
```

Out[52]: <seaborn.axisgrid.FacetGrid at 0x272a167c188>



- Observation:
  - extreme weather should cause delays logically, however, the effect is probably very local and minimal

Data preparation

In [53]:
```
# Basic Libraries
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt # we only need pyplot
from plotnine import *
sb.set() # set the default Seaborn style for graphics
```

In [54]:
```
# read data
flight_train_data=pd.read_csv('train.csv')
flight_test_data=pd.read_csv('test.csv')
# combine train n test
data_preprocessing=pd.concat([flight_train_data,flight_test_data],axis=0,sort=False).re
# drop index columns
data_preprocessing=data_preprocessing.drop(['index'],axis=1)
```

time-based columns

In [55]:
```
# extract only the numerics from these variable
for var in ['Month','DayofMonth','DayOfWeek']:
    data_preprocessing[var]=data_preprocessing[var].apply(lambda x: x.split('-')[1])
```

In [56]:
```
# bin departure time
bins=[]
for i in range(24):
    tuple_bin=(i*100,i*100+59)
    bins.append(tuple_bin)
interval_bins = pd.IntervalIndex.from_tuples(bins)
data_preprocessing['DepTime_binned']=pd.cut(data_preprocessing['DepTime'],interval_bins
data_preprocessing['DepTime_binned']=data_preprocessing['DepTime_binned'].map(dict(zip(
```

In [57]:
```
# convert time-base columns to int
for var in ['Month','DepTime_binned','DayofMonth','DayOfWeek']:
    data_preprocessing[var]=data_preprocessing[var].astype(int)
```

In [58]:
```
# function that converts variable to a cyclical feature
def encode_cyclical_feature(data, col):
    max_val=data[col].max()
    data[col + '_sin'] = np.sin(2 * np.pi * data[col]/max_val)
    data[col + '_cos'] = np.cos(2 * np.pi * data[col]/max_val)
    return data
```

In [59]:
```
# convert variables to cyclical
for var in ['Month','DepTime_binned','DayofMonth','DayOfWeek']:
    encode_cyclical_feature(data_preprocessing,var)
```

In [60]:
```
# scatter plot to check conversion
scatterplot_list=[('Month_sin', 'Month_cos'), ('DepTime_binned_sin', 'DepTime_binned_co
f, axes = plt.subplots(4,1 , figsize=(5,15))
for i,pair in enumerate(scatterplot_list):
    sb.scatterplot(data=data_preprocessing,x=pair[0],y=pair[1],ax=axes[i])
```

- Action:
  - convert time-based columns to a cycical feature with 2 columns: sine and cosine.
    - this way i avoid having to one hot encode every month and day which will increase dimentiality drastically

new feature: days from holiday

In [61]:
```
# get list of holidays
import holidays
holiday_dates=pd.to_datetime(list(holidays.UnitedStates(years=2018).keys()))
```

In [62]:
```
# create a date column
data_preprocessing['date']=pd.to_datetime('2018/'+data_preprocessing.Month.astype(str)+
```

In [63]:
```
# list all dates in order
all_dates_list=pd.to_datetime(data_preprocessing['date'].sort_values().unique())
# find the corresponding number of days from holiday
days_from_holiday=[]
for date in all_dates_list:
    smallest_difference=999
    for holiday in holiday_dates:
        difference=(date-holiday).days
        if(abs(difference)<smallest_difference):
            smallest_difference=difference
    days_from_holiday.append(smallest_difference)
# dictionary used for mapping
days_from_holiday_mapping=dict(zip(all_dates_list,days_from_holiday))
# .map() method to map every date to their corresponding number of days from holiday
data_preprocessing=data_preprocessing.assign(days_from_holiday=data_preprocessing['date
```

- Action:
  - created new feature, days_from_holiday, because dates closer to holidays are more likely to be delayed

UniqueCarrier

In [64]:
```
# labels a categorical variable by their rank based on frequency
def labelcount_encode(X, categorical_features, ascending=False):
    print('LabelCount encoding: {}'.format(categorical_features))
    X_ = pd.DataFrame()
    for cat_feature in categorical_features:
        cat_feature_value_counts = X[cat_feature].value_counts()
        value_counts_list = cat_feature_value_counts.index.tolist()
        if ascending:
            # for ascending ordering
            value_counts_range = list(
                reversed(range(len(cat_feature_value_counts))))
        else:
            # for descending ordering
            value_counts_range = list(range(len(cat_feature_value_counts)))
        labelcount_dict = dict(zip(value_counts_list, value_counts_range))
        X_[cat_feature] = X[cat_feature].map(
            labelcount_dict)
    X_ = X_.add_suffix('_labelcount_encoded')
    if ascending:
        X_ = X_.add_suffix('_ascending')
    else:
        X_ = X_.add_suffix('_descending')
    X_ = X_.astype(np.uint32)
    return X_
```

In [65]:
```
# encode UniqueCarrier by frequency rank
data_preprocessing=pd.concat([data_preprocessing,labelcount_encode(data_preprocessing,[
```

```
LabelCount encoding: ['UniqueCarrier']
```

- Action:
  - i will encode by the rank of their frequency as i noticed from earlier visauilizations that it does predict delay to an extent
  - this avoids one hot encoding that can cause high dimentiality
  - also, this remedies the problem where carriers found in test set are not found in training set

Origin_Dest

In [66]:
```
# combining Origin n Dest
data_preprocessing['Origin-Dest']=data_preprocessing['Origin']+data_preprocessing['Dest
# frequency encode
data_preprocessing=pd.concat([data_preprocessing,labelcount_encode(data_preprocessing,[
```

```
LabelCount encoding: ['Origin-Dest']
```

- Action:
  - encoded Origin_Dest by the rank of their frequencies
  - as this variable has high cardinality and its effect on delays is quite minimal, i want to keep their noise and dimentiality to the minimum by combining to one variable and frequency encoding

drop remaining variables

In [67]:
```
data_preprocessing.drop(['Month', 'DayofMonth', 'DayOfWeek', 'DepTime', 'UniqueCarrier'
```

- Action:
  - dropped because i won't use these variables in the models

scale variables

In [68]:
```
# define function that applies normalization
def normalization(target_data,target_variable):
    target_series=target_data[target_variable]
    minimum=target_series.min()
    maximum=target_series.max()
    resultant_series=(target_series-minimum)/(maximum-minimum)
    return resultant_series
```

In [69]:
```
for var in ['Distance','days_from_holiday','Origin-Dest_labelcount_encoded_ascending','
    data_preprocessing[var]=normalization(data_preprocessing,var)
```

- Action:
  - normalized variables so features are in the same scale. speed and performance may improve for certain models

encode response

In [70]:
```
response_encoding_map={'Y':1,'N':0}
data_preprocessing['dep_delayed_15min']=data_preprocessing['dep_delayed_15min'].map(res
```

separate to train and test set

In [71]:
```
test_set=data_preprocessing[data_preprocessing['dep_delayed_15min'].isna()]
training_set=data_preprocessing[~data_preprocessing['dep_delayed_15min'].isna()]
```

In [72]:
```
# separate response from predictors
y=training_set['dep_delayed_15min']
X=training_set.drop(['dep_delayed_15min'],axis=1)
test_set=test_set.drop(['dep_delayed_15min'],axis=1)
```

In [96]:
```
# safe a copy of the columns sequence
column_sequence=test_set.columns
```

In [73]:
```
X.head()
```

Out[73]:

	Distance	Month_sin	Month_cos	DepTime_binned_sin	DepTime_binned_cos	DayofMonth_sin	DayofMont
0	0.142336	-0.866025	-5.000000e-01	-0.887885	0.460065	-0.897805	-0.4
1	0.163017	0.866025	-5.000000e-01	-0.816970	-0.576680	-0.790776	-0.6
2	0.078264	-1.000000	-1.836970e-16	-0.631088	-0.775711	0.394356	0.9
3	0.170722	-0.500000	8.660254e-01	0.398401	-0.917211	-0.937752	0.3
4	0.079684	-0.866025	5.000000e-01	-0.979084	0.203456	0.988468	0.1

In [74]:
```
test_set.head()
```

Out[74]:

	Distance	Month_sin	Month_cos	DepTime_binned_sin	DepTime_binned_cos	DayofMonth_sin
100000	0.115166	-5.000000e-01	-8.660254e-01	0.997669	-0.068242	-0.937752
100001	0.244323	8.660254e-01	-5.000000e-01	0.942261	-0.334880	-0.299363
100002	0.110908	-2.449294e-16	1.000000e+00	0.997669	-0.068242	0.394356
100003	0.070357	1.000000e+00	6.123234e-17	-0.942261	-0.334880	-0.937752
100004	0.046229	1.224647e-16	-1.000000e+00	-0.816970	-0.576680	0.937752

Borderline SMOTE + undersampling

- since the response classes are imbalanced i want to apply SMOTE to balance the classes
- this over samples the minority class

```
  - essentially, a line is drawn between minority examples that a close tog
ether and a new example along this line is augmented
  - furthermore, i will try borderline sampling only augments minority exam
ples that are **harder to classify** i.e. examples that are along the decis
ion boundary(hard to discern whether its going to be delayed or not)
```

- it has been suggested in certain studies that combining SMOTE **with undersampling may be better**, so i will try undersampling the majority class

In [75]:
```
from numpy import mean
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.tree import DecisionTreeClassifier
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import BorderlineSMOTE,SMOTE
from imblearn.under_sampling import RandomUnderSampler
```

In [76]:
```
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, ExtraT
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold, cross_val_score,GridSearchCV,learn
```

#apply Borderline smote with undersampling

k_values = [1, 2, 3, 4, 5, 6, 7] for k in k_values:

```
# define pipeline
model = DecisionTreeClassifier()
over = BorderlineSMOTE(sampling_strategy=0.5, k_neighbors=k)
under = RandomUnderSampler(sampling_strategy=0.5)
steps = [('over', over), ('under', under), ('model', model)]
pipeline = Pipeline(steps=steps)
# evaluate pipeline
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(pipeline, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
score = mean(scores)
print('> k=%d, Mean Accuracy: %.3f' % (k, score))
```

In [9]:
```
# performance with SMOTE and undersampling
from IPython.display import Image
Image(filename='Images\SMOTE+undersampling performance.JPG')
```

Out[9]:
```
> k=1, Mean Accuracy: 0.715
> k=2, Mean Accuracy: 0.714
> k=3, Mean Accuracy: 0.712
> k=4, Mean Accuracy: 0.712
> k=5, Mean Accuracy: 0.713
> k=6, Mean Accuracy: 0.712
> k=7, Mean Accuracy: 0.712
```

- Action:
  - trained a simple model to descern what is the optimal number of **k neighbours**.
  - there **isn't much difference**, 1 seems to be best

#without SMOTE

model = DecisionTreeClassifier()

#cross validation

cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1) scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1) print('Mean accuracy: %.3f' % mean(scores))

In [78]:
```
# performance without SMOTE
Image(filename='Images\without SMOTE performance.JPG')
```

Out[78]:

```
Mean accuracy: 0.719
```

#apply SMOTE only

model = DecisionTreeClassifier() oversample = SMOTE() X_Smote, y_Smote = oversample.fit_resample(X, y)

#cross validation

cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1) scores = cross_val_score(model, X_Smote, y_Smote, scoring='accuracy', cv=cv, n_jobs=-1) print('Mean accuracy: %.3f' % mean(scores))

In [79]:
```
# performance with SMOTE
Image(filename='Images\with SMOTE performance.PNG')
```

Out[79]:

```
Mean accuracy: 0.811
```

In [80]:
```
# apply Borderline SMOTE only
model = DecisionTreeClassifier()
oversample = BorderlineSMOTE()
X_BSmote, y_BSmote = oversample.fit_resample(X, y)

# cross validation
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(model, X_BSmote, y_BSmote, scoring='accuracy', cv=cv, n_jobs=-
print('Mean accuracy: %.3f' % mean(scores))
```

```
Mean accuracy: 0.813
```

- Observation:
    - looks like applying undersampling together with SMOTE actually **worsens** model performance
    - applying **SMOTE is indeed much better than without**
    - applying **BorderlineSMOTE performed bette**r than regular SMOTE

Training the models

- i will use only Borderline SMOTE for the remaining models

In [81]:
```
# stratified k fold to preserve the class proportions in every fold
kfold=StratifiedKFold(n_splits=10)
```

In [88]:
```
# training random forest model
random_state=2
classifier=RandomForestClassifier(random_state=random_state,n_jobs=-1,n_estimators=500)
cv_results=cross_val_score(classifier,X_BSmote, y_BSmote,cv=kfold,n_jobs=-1)
```

In [87]:
```
print("Cross Validation Score:",mean(cv_results))
```

```
Cross Validation Score: 0.8830628314152346
```

- Action:
  - for this dataset, training the model takes too long, so i will **skip hyperparameter** tuning which will take even longer

Learning Curves

In [89]:
```
def plot_learning_curve(estimator,title,X,y,ylim=None,cv=None,n_jobs=-1,train_sizes=np.

    plt.figure(figsize=(12, 8))
    plt.title(title)
    plt.xlabel('Training Examples')
    plt.ylabel('Score')

    train_sizes,train_scores,test_scores=learning_curve(estimator ,X , y,
                                                        cv=cv,
                                                        n_jobs=n_jobs,
                                                        train_sizes=train_sizes)

    train_scores_mean=np.mean(train_scores,axis=1)
    train_scores_std=np.std(train_scores,axis=1)
    test_scores_mean=np.mean(test_scores,axis=1)
    test_scores_std=np.std(test_scores,axis=1)

    plt.grid()

    plt.fill_between(train_sizes,
                     train_scores_mean-train_scores_std,
                     train_scores_mean+train_scores_std, alpha= 0.1 ,color='y')
    plt.fill_between(train_sizes,
                     test_scores_mean-test_scores_std,
                     test_scores_mean+test_scores_std, alpha= 0.1 ,color='b')

    plt.plot(train_sizes,train_scores_mean,'o-',color='y',
            label='Training scores')
    plt.plot(train_sizes,test_scores_mean,'o-',color='b',
            label='Cross validation scores')

    plt.legend(loc='best')
    return plt
```

In [90]:
```
plot_learning_curve(classifier,'Random Forest Learning Curve',
                    X_BSmote, y_BSmote,
                    cv=kfold)
```

Out[90]:
```
<module 'matplotlib.pyplot' from 'C:\\Users\\tanch\\AppData\\Roaming\\Python\\Pytho
n37\\site-packages\\matplotlib\\pyplot.py'>
```

- Obersvation:
  - a significant differnce in training and cross validation scores suggest significant over fitting

training on the whole training set

In [91]:
```
# random forest model
random_state=2
ranForClassifier=RandomForestClassifier(random_state=random_state,n_jobs=-1,n_estimator
ranForClassifier.fit(X_BSmote, y_BSmote)
```

Out[91]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=-1, oob_score=False, random_state=2, verbose=0,
                       warm_start=False)
```

In [116]:
```
# making probability predictions on the test set
test_predictions=ranForClassifier.predict_proba(test_set)
test_predictions
```

Out[116]:
```
array([[0.994, 0.006],
       [0.928, 0.072],
       [0.966, 0.034],
       ...,
       [0.688, 0.312],
       [0.834, 0.166],
       [0.882, 0.118]])
```

- Observation: the **probablity of being delayed 15 min is on index 1**

In [117]:
```
# extract the probablity of being delayed 15 min
dep_delayed_15min=[]
for predictions in test_predictions:
    dep_delayed_15min.append(predictions[1])
dep_delayed_15min=pd.Series(dep_delayed_15min,name='dep_delayed_15min')
```

In [121]:
```
# extract the id column
test_set_id_column=pd.Series(range(len(test_set)),name='id')
```

In [122]:
```
# finalising results
results=pd.concat([test_set_id_column,dep_delayed_15min],axis=1)
results
```

Out[122]:

	id	dep_delayed_15min
0	0	0.006
1	1	0.072
2	2	0.034
3	3	0.266
4	4	0.512
...	...	...
99995	99995	0.040
99996	99996	0.146
99997	99997	0.312
99998	99998	0.166
99999	99999	0.118

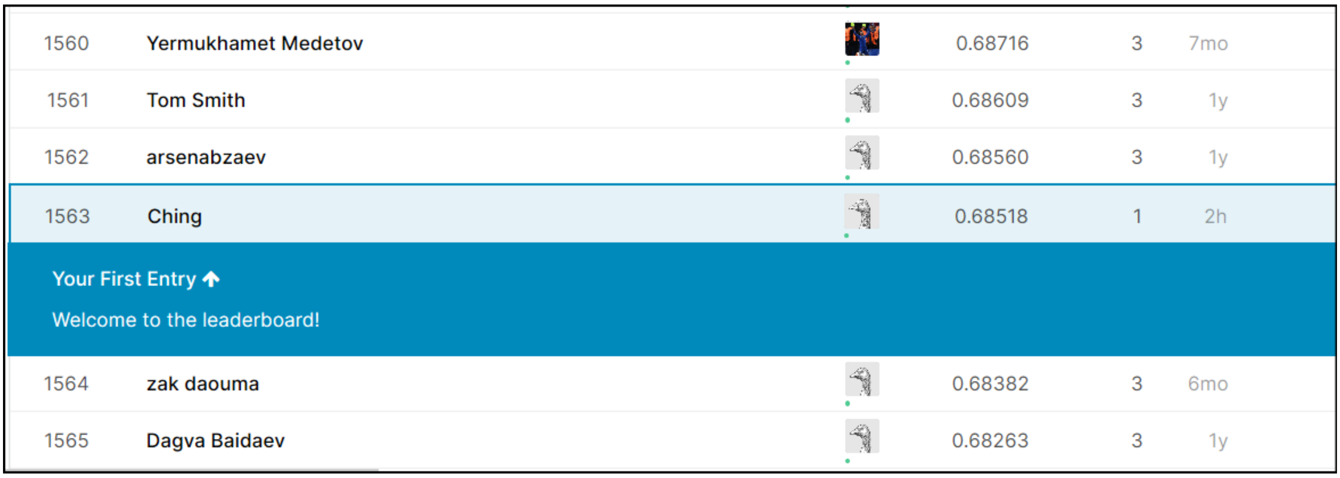
100000 rows × 2 columns

In [123]:
```
results.to_csv('randomForestPredictions.csv',index=False)
```

First try results

In [15]:
```python
Image(filename='Images/first_try_results.png')
```

Out[15]:



1560	Yermukhamet Medetov	0.68716	3	7mo
1561	Tom Smith	0.68609	3	1y
1562	arsenabzaev	0.68560	3	1y
1563	Ching	0.68518	1	2h
Your First Entry ↑ Welcome to the leaderboard!				
1564	zak daouma	0.68382	3	6mo
1565	Dagva Baidaev	0.68263	3	1y

- performance on the training set was not very good on the first try

Feature importances

In [98]:
```python
X_BSmote=pd.DataFrame(X_BSmote,columns=column_sequence)
```

In [99]:
```python
f, axes = plt.subplots(1,1 , figsize=(10, 10))
indices=np.argsort(ranForClassifier.feature_importances_)[::-1]
g=sb.barplot(y=X_BSmote.columns[indices],x=ranForClassifier.feature_importances_[indice
g.set_ylabel('Features',fontsize=15)
g.tick_params(labelsize=10)
g.set_title('Feature Importance',fontsize=15)
```

Out[99]:
```
Text(0.5, 1.0, 'Feature Importance')
```

- Observation:
  - as expected, **departure time is the strongest predictor**
  - carriers and distance a also quite important