doyleax / **West-Nile-Virus-Prediction**

master West-Nile-Virus-Prediction / **Final-NB.ipynb** Go to file ...

doyleax renamed clean jupyter notebook Latest commit cc9e98a on 28 Apr 2017 History

1 contributor

2.11 MB Download

Predicting West Nile Virus - Kaggle Competition

Jenny Doyle, Joseph Brown, Mark Mummert

Tasks (https://trello.com/b/EsEm4u65/kaggle-group-project) Presentation (https://docs.google.com/presentation/d/1OYMH0lvh7J6ulr0cuL9AxoyFtUaxgkqxYWKBzyuXG-A/edit?usp=sharing) Write-up (https://docs.google.com/document/d/1OQLiP7EnFjc8AtlFAX2H-H3zBbirbs6enUWPgddmggY/edit)

In [1]:
```
import pandas as pd
from matplotlib import pyplot as plt
import numpy as np
# pip install pandas-profiling
import pandas_profiling as pdp
import seaborn as sns
%matplotlib inline
import time
import datetime

traps = pd.read_csv('assets/train.csv')
test = pd.read_csv('assets/test.csv')
spray = pd.read_csv('assets/spray.csv')
weather = pd.read_csv('assets/weather.csv')
```

```
//anaconda/lib/python2.7/site-packages/matplotlib/__init__.py:1401: UserWarning:  This call to matplotlib.use() has no effect
because the backend has already been chosen;
matplotlib.use() must be called *before* pylab, matplotlib.pyplot,
or matplotlib.backends is imported for the first time.

  warnings.warn(_use_error_msg)
```

EDA

Traps

In [2]:
```
pdp.ProfileReport(traps)
```

Out[2]:

verview

aset info

mber of variables	12
mber of observations	10506
al Missing (%)	0.0%
al size in memory	985.0 KiB
erage record size in memory	96.0 B

ables types

meric	6
tegorical	6
te	0
t (Unique)	0
jected	0

nings

- `Address` has a high cardinality: 138 distinct values **Warning**
- `AddressNumberAndStreet` has a high cardinality: 138 distinct values **Warning**
- `Date` has a high cardinality: 95 distinct values **Warning**
- `Street` has a high cardinality: 128 distinct values **Warning**
- `Trap` has a high cardinality: 136 distinct values **Warning**
- `WnvPresent` has 9955 / 94.8% zeros
- Dataset has 813 duplicate rows **Warning**

riables

lress

tinct count	138
ique (%)	1.3%
sing (%)	0.0%
sing (n)	0

D Terminal 5, O'Hare International Airport, Chicago, IL 60666, USA	750
uth Doty Avenue, Chicago, IL, USA	542
uth Stony Island Avenue, Chicago, IL, USA	314
her values (135)	8900

lressAccuracy

: count	4
(%)	0.0%
ı (%)	0.0%
ı (n)	0
(%)	0.0%
(n)	0

	7.8195
m	3
ım	9
%)	0.0%

lressNumberAndStreet

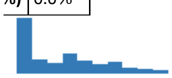
stinct count	138
ique (%)	1.3%
ssing (%)	0.0%
ssing (n)	0

)0 W OHARE AIRPORT, Chicago, IL	750
)0 S DOTY AVE, Chicago, IL	542
)0 S STONY ISLAND AVE, Chicago, IL	314
ıer values (135)	8900

:k

: count	64
(%)	0.6%
ı (%)	0.0%
ı (n)	0
(%)	0.0%
(n)	0

	35.688
m	10
ım	98
%)	0.0%



ə

stinct count	95
ique (%)	0.9%
ssing (%)	0.0%
ssing (n)	0

)7-08-01	551
)7-08-15	276
13-08-01	186
ıer values (92)	9493

tude

: count	138
(%)	1.3%
ı (%)	0.0%
ı (n)	0
(%)	0.0%

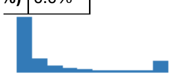
(n)	0
	41.841
m	41.645
ım	42.017
%)	0.0%

gitude

: count	138
(%)	1.3%
ı (%)	0.0%
ı (n)	0
(%)	0.0%
(n)	0
	-87.7
m	-87.931
ım	-87.532
%)	0.0%

ıMosquitos

: count	50
(%)	0.5%
ı (%)	0.0%
ı (n)	0
(%)	0.0%
(n)	0
	12.854
m	1
ım	50
%)	0.0%



cies

;tinct count	7
ique (%)	0.1%
;sing (%)	0.0%
;sing (n)	0
ILEX PIPIENS/RESTUANS	4752
ILEX RESTUANS	2740
ILEX PIPIENS	2699
ıer values (4)	315

et

;tinct count	128
ique (%)	1.2%
;sing (%)	0.0%
;sing (n)	0
OHARE AIRPORT	750
OOTY AVE	542
;TONY ISLAND AVE	347
ıer values (125)	8867

)

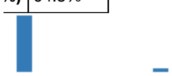
stinct count	136
ique (%)	1.3%
ssing (%)	0.0%
ssing (n)	0

)0	750
15	542
38	314
her values (133)	8900

/Present

: count	2
(%)	0.0%
ı (%)	0.0%
ı (n)	0
(%)	0.0%
(n)	0

	0.052446
m	0
ım	1
%)	94.8%



ample

Date	Address	Species	Block	Street	Trap	AddressNumberAndStreet	Latitude	Longitude	AddressAccuracy	NumMosquito
2007-05-29	4100 North Oak Park Avenue, Chicago, IL 60634,...	CULEX PIPIENS/RESTUANS	41	N OAK PARK AVE	T002	4100 N OAK PARK AVE, Chicago, IL	41.954690	-87.800991	9	1
2007-05-29	4100 North Oak Park Avenue, Chicago, IL 60634,...	CULEX RESTUANS	41	N OAK PARK AVE	T002	4100 N OAK PARK AVE, Chicago, IL	41.954690	-87.800991	9	1
2007-05-29	6200 North Mandell Avenue, Chicago, IL 60646, USA	CULEX RESTUANS	62	N MANDELL AVE	T007	6200 N MANDELL AVE, Chicago, IL	41.994991	-87.769279	9	1
2007-05-29	7900 West Foster Avenue, Chicago, IL 60656, USA	CULEX PIPIENS/RESTUANS	79	W FOSTER AVE	T015	7900 W FOSTER AVE, Chicago, IL	41.974089	-87.824812	8	1
2007-05-29	7900 West Foster Avenue, Chicago, IL 60656, USA	CULEX RESTUANS	79	W FOSTER AVE	T015	7900 W FOSTER AVE, Chicago, IL	41.974089	-87.824812	8	4

From this profile report of traps, there are a few things we found important and will deal with:

- the multiple address features seem irrelevant with Latitude and Longitude. Remove them
- WnvPresent has nearly 95% zero!!! We will need to stratify our training data so that the negative class doesn't dominate the results
- Species has 7 categorical values: create dummies
- Date feature should be converted to date datatype
- 813 duplicate rows: We know from the data descriptions that observations are capped at 50 mosquitos, so it's definitely possible that a single observation spans a couple of records. We'll leave the duplicates for this reason, and sum up the number of mosquitos with a groupby.

In [2]:
```
## We can tackle the multiple addresses and the grouping in this one step
traps = traps[['Trap',
               'Latitude',
               'Longitude',
               'Date',
               'Species',
               'WnvPresent',
               'NumMosquitos']].groupby(['Trap',
                                         'Latitude',
                                         'Longitude',
                                         'Date',
                                         'Species',
                                         'WnvPresent']).agg({'NumMosquitos':np.sum}).reset_index()

feats = traps.columns

## get species dummies and add to traps df
traps = pd.get_dummies(traps, columns=['Species'])
```

```
traps = pd.get_dummies(traps, columns=['Species'])

## convert to date
traps.Date = pd.to_datetime(traps.Date)
```

Let's look at the features that we'll have when we run our test data through the models:

In [3]:
```
test.columns
```

Out[3]:
```
Index([u'Id', u'Date', u'Address', u'Species', u'Block', u'Street', u'Trap',
       u'AddressNumberAndStreet', u'Latitude', u'Longitude',
       u'AddressAccuracy'],
      dtype='object')
```

In [4]:
```
# The test data doesn't include NumMosquitos...
# this means we should drop this column from traps
# and then drop the duplicates

traps.drop('NumMosquitos',axis=1,inplace=True)
traps.drop_duplicates(inplace=True)


## Might as well go ahead and perform the same modifications on the test data

# remove the redundant address features from test
test = test[feats.drop(['WnvPresent','NumMosquitos'])]

## get species dummies and add to traps df
test = pd.get_dummies(test, columns=['Species'])

## convert to date
test.Date = pd.to_datetime(test.Date)
```

Spray

In [6]:
```
pdp.ProfileReport(spray)
```

Out[6]:

verview

aset info

mber of variables	4
mber of observations	14835
al Missing (%)	1.0%
al size in memory	463.7 KiB
erage record size in memory	32.0 B

ables types

meric	2
tegorical	2
te	0
t (Unique)	0
jected	0

nings

- Time has 584 / 3.9% missing values **Missing**
- Time has a high cardinality: 8584 distinct values **Warning**
- Dataset has 541 duplicate rows **Warning**

ariables

e

tinct count	10
ique (%)	0.1%
ssing (%)	0.0%
ssing (n)	0

13-08-15	2668
13-08-29	2302
13-07-17	2202
her values (7)	7663

tude

count	12887
(%)	86.9%
(%)	0.0%
(n)	0
(%)	0.0%
(n)	0

	41.905
m	41.714
ım	42.396
%)	0.0%

gitude

t count	13007
(%)	87.7%
ı (%)	0.0%
ı (n)	0
(%)	0.0%
(n)	0
	-87.737
m	-88.096
ım	-87.587
%)	0.0%

e

stinct count	8584
ique (%)	60.2%
ssing (%)	3.9%
ssing (n)	584

4:32 PM	541
9:06 PM	5
5:36 PM	5
ıer values (8580)	13700
ssing)	584

ımple

Date	Time	Latitude	Longitude
2011-08-29	6:56:58 PM	42.391623	-88.089163
2011-08-29	6:57:08 PM	42.391348	-88.089163
2011-08-29	6:57:18 PM	42.391022	-88.089157
2011-08-29	6:57:28 PM	42.390637	-88.089158
2011-08-29	6:57:38 PM	42.390410	-88.088858

This is a really simple dataset. There are missing values in time, but it doesn't seem like a significant feature as it's too specific and variable. We will exclude Time, and don't have any modifications to make aside from converting the Date feature into date type.

In [5]:
```
spray.Date = pd.to_datetime(spray.Date)
```

In [6]:
```
spray.duplicated().sum()
```

Out[6]: 541

In [7]:
```
# Drop the duplicate records
spray.drop_duplicates(inplace=True)
```

Weather

In [10]:
```
pdp.ProfileReport(weather)
```

Out[10]:

verview

ıset info

mber of variables	22

mber of variables	22
mber of observations	2944
al Missing (%)	0.0%
al size in memory	506.1 KiB
erage record size in memory	176.0 B

ables types

meric	5
tegorical	15
te	0
t (Unique)	0
jected	2

nings

`AvgSpeed` has a high cardinality: 178 distinct values **Warning**
`CodeSum` has a high cardinality: 98 distinct values **Warning**
`Date` has a high cardinality: 1472 distinct values **Warning**
`DewPoint` is highly correlated with `Tmin` (ρ = 0.90436) **Rejected**
`PrecipTotal` has a high cardinality: 168 distinct values **Warning**
`SeaLevel` has a high cardinality: 102 distinct values **Warning**
`StnPressure` has a high cardinality: 104 distinct values **Warning**
`Sunrise` has a high cardinality: 122 distinct values **Warning**
`Sunset` has a high cardinality: 119 distinct values **Warning**
`Tavg` has a high cardinality: 60 distinct values **Warning**
`Water1` has constant value M **Rejected**

riables

Speed

tinct count	178
ique (%)	6.0%
ssing (%)	0.0%
ssing (n)	0

	63
	60
	55
ner values (175)	2766

leSum

tinct count	98
ique (%)	3.3%
ssing (%)	0.0%
ssing (n)	0

	1609
	296
BR	238
ner values (95)	801

l

tinct count	31
ique (%)	1.1%
ssing (%)	0.0%
ssing (n)	0

	1147
	138
	117
ner values (28)	1542

e

tinct count	1472
ique (%)	50.0%
ssing (%)	0.0%

ssing (n)	0

13-06-02	2
09-09-14	2
14-05-31	2
her values (1469)	2938

art

stinct count	42
ique (%)	1.4%
ssing (%)	0.0%
ssing (n)	0

	1472
	93
	84
her values (39)	1295

th

stinct count	2
ique (%)	0.1%
ssing (%)	0.0%
ssing (n)	0

1472
1472

~~Point~~

variable is highly correlated with `Tmin` and should be ignored for analysis

rrelation	0.90436

t

stinct count	31
ique (%)	1.1%
ssing (%)	0.0%
ssing (n)	0

	1870
	88
	86
her values (28)	900

cipTotal

stinct count	168
ique (%)	5.7%
ssing (%)	0.0%
ssing (n)	0

0	1577
	318
1	127
her values (165)	922

ultDir

count	36
(%)	1.2%
(%)	0.0%
(n)	0
(%)	0.0%
(n)	0

	17.495
m	1
ım	36
%)	0.0%

ultSpeed

count	190
(%)	6.5%
(%)	0.0%
(n)	0
(%)	0.0%
(n)	0

	6.9607
m	0.1
ım	24.1
%)	0.0%

Level

stinct count	102
ique (%)	3.5%
ssing (%)	0.0%
ssing (n)	0

00	96
94	85
98	85
her values (99)	2678

wFall

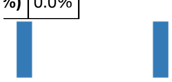
stinct count	4
ique (%)	0.1%
ssing (%)	0.0%
ssing (n)	0

	1472
	1459
	12

ion

count	2
(%)	0.1%
(%)	0.0%
(n)	0
(%)	0.0%
(n)	0

	1.5
m	1
ım	2
%)	0.0%



Pressure

stinct count	104

ique (%)	3.5%
ssing (%)	0.0%
ssing (n)	0

34	128
28	124
26	123
her values (101)	2569

rise

stinct count	122
ique (%)	4.1%
ssing (%)	0.0%
ssing (n)	0

	1472
l6	104
l7	64
her values (119)	1304

set

stinct count	119
ique (%)	4.0%
ssing (%)	0.0%
ssing (n)	0

	1472
31	96
30	56
her values (116)	1320

g

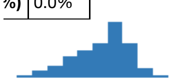
stinct count	60
ique (%)	2.0%
ssing (%)	0.0%
ssing (n)	0

	138
	117
	117
her values (57)	2572

ax

t count	63
(%)	2.1%
j (%)	0.0%
j (n)	0
(%)	0.0%
(n)	0

	76.166
m	41
um	104
%)	0.0%



n

count	54
(%)	1.8%
(%)	0.0%
(n)	0
(%)	0.0%
(n)	0

	57.81
m	29
ım	83
%)	0.0%

~~er1~~

variable is constant and should be ignored for analysis

nstant value	M

Bulb

tinct count	48
ique (%)	1.6%
ssing (%)	0.0%
ssing (n)	0

	135
	131
	129
ner values (45)	2549

ample

Station	Date	Tmax	Tmin	Tavg	Depart	DewPoint	WetBulb	Heat	Cool	Sunrise	Sunset	CodeSum	Depth	Water1	SnowFall	PrecipTotal	StnPressure	Sea
1	2007-05-01	83	50	67	14	51	56	0	2	0448	1849		0	M	0.0	0.00	29.10	29.8
2	2007-05-01	84	52	68	M	51	57	0	3	-	-		M	M	M	0.00	29.18	29.8
1	2007-05-02	59	42	51	-3	42	47	14	0	0447	1850	BR	0	M	0.0	0.00	29.38	30.0
2	2007-05-02	60	43	52	M	42	47	13	0	-	-	BR HZ	M	M	M	0.00	29.44	30.0
1	2007-05-03	66	46	56	2	40	48	9	0	0446	1851		0	M	0.0	0.00	29.39	30.1

Important notes from the profile report:

- Need to convert Date to actual date datatype
- The weather data has 2 weather observations per date, one from station 1 and the other from station 2. Maybe we only need data from one station. After looking at the sample of the data in the profile report, it looks like there might be a difference in the amount of 'M'==missing values
- Several features should be numeric datatypes, but contain indicators like 'T' or 'M' that need to be removed. T = trace, M = missing. Need to clean up these features
- CodeSum: any code in this feature indicates a significant weather event, so we can turn this into a binary feature indicating whether or not a significant weather event occurred
- Tavg has more missing values than Tmin, Tmax, so we will just set it to the average of Tmin and Tmax

In [8]:
```
weather.Date = pd.to_datetime(weather.Date)
```

In [9]:
```
# skip the numeric columns, because they can't contain the 'M' string
check_missing_values = ['Depart','Heat','Cool','Sunrise','Sunset','Depth','Water1','SnowFall']
for col in weather[check_missing_values]:
    station_1 = len(weather[(weather[col].str.contains('\D')) & (weather.Station==1)])
    print col + ' has ' + str(station_1) + ' missing values at station 1'
    station_2 = len(weather[(weather[col].str.contains('\D')) & (weather.Station==2)])
    print col + ' has ' + str(station_2) + ' missing values at station 2'
    print ''
```

```
Depart has 1271 missing values at station 1
Depart has 1472 missing values at station 2

Heat has 0 missing values at station 1
Heat has 11 missing values at station 2

Cool has 1096 missing values at station 1
Cool has 1021 missing values at station 2
```

```
Sunrise has 0 missing values at station 1
Sunrise has 1472 missing values at station 2

Sunset has 0 missing values at station 1
Sunset has 1472 missing values at station 2

Depth has 0 missing values at station 1
Depth has 1472 missing values at station 2

Water1 has 1472 missing values at station 1
Water1 has 1472 missing values at station 2

SnowFall has 1472 missing values at station 1
SnowFall has 1472 missing values at station 2
```

It looks like station 2 consistently has more missing values, so let's stick to using station 1 as our weather source.

In [10]:
```
weather = weather[weather.Station==1].drop('Station',axis=1)
```

Actually, a bunch of the features are 0 and won't give us any information. We'll remove them:

In [11]:
```
exclude = ['Depart','Heat','Cool','Sunrise','Sunset','Depth','Water1','SnowFall']
include = weather.columns.drop(exclude)
weather = weather[include]

weather.columns
```

Out[11]:
```
Index([u'Date', u'Tmax', u'Tmin', u'Tavg', u'DewPoint', u'WetBulb', u'CodeSum',
       u'PrecipTotal', u'StnPressure', u'SeaLevel', u'ResultSpeed',
       u'ResultDir', u'AvgSpeed'],
      dtype='object')
```

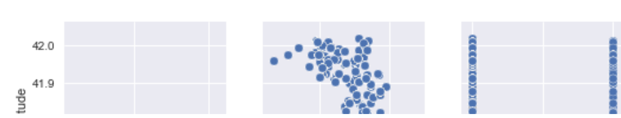
In [12]:
```
# clean up features that should be numeric

# the PrecipTotal column contains the letter 'T' in some rows
# this indicates a 'trace' amount of precipitation, which is
# defined as less than 0.005
# 'M' indicates missing data

def clean_col(column):
    weather[column] = weather[column].str.replace('T','0.005')
    weather[column] = weather[column].str.replace('M','0.0')
    weather[column] = weather[column].astype(float)



clean_col('Tavg')
clean_col('PrecipTotal')
clean_col('WetBulb')
clean_col('StnPressure')
clean_col('SeaLevel')
clean_col('AvgSpeed')
# columns = ['Tavg','PrecipTotal','WetBulb','StnPressure','SeaLevel','AvgSpeed']
# for col in columns:
#     clean_col(col)

# If the CodeSum contains letters, they signify some type
# of significant weather event. Let's instead flag these as 1
# and then 0 for the values that are just whitespace
weather.CodeSum = weather.CodeSum.str.strip()
weather.CodeSum[weather.CodeSum.str.contains('^\w')] = '1'
weather.CodeSum[weather.CodeSum!='1'] = '0'
weather.CodeSum = weather.CodeSum.astype(float)

# fill in missing Tavg by just taking the avg of Tmin and Tmax
# while this is not how Tavg is calculated, but it's probably close
weather['Tavg'][weather.Tavg==0] = (weather.Tmin + weather.Tmax) / 2
```

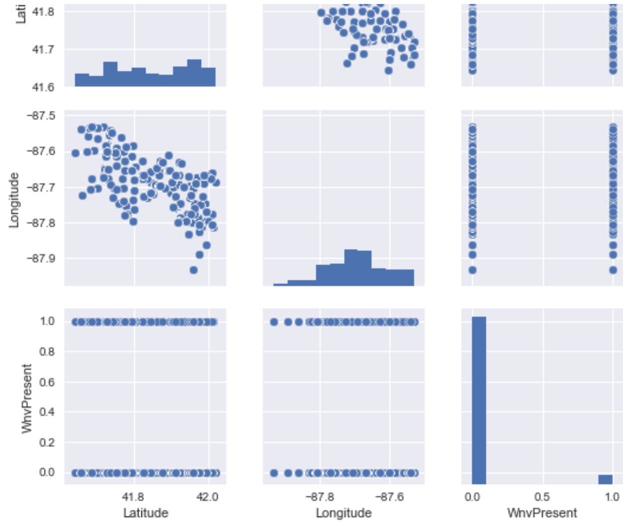
```
/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:29: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:30: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:35: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
```

Modified Features -- Look at pairplots

In [13]:
```
no_dummies = [x for x in traps.columns if not 'Species_' in x]
sns.pairplot(traps[no_dummies])
```

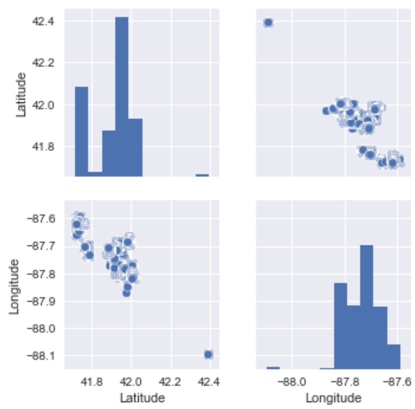
Out[13]:
```
<seaborn.axisgrid.PairGrid at 0x115fa2dd0>
```





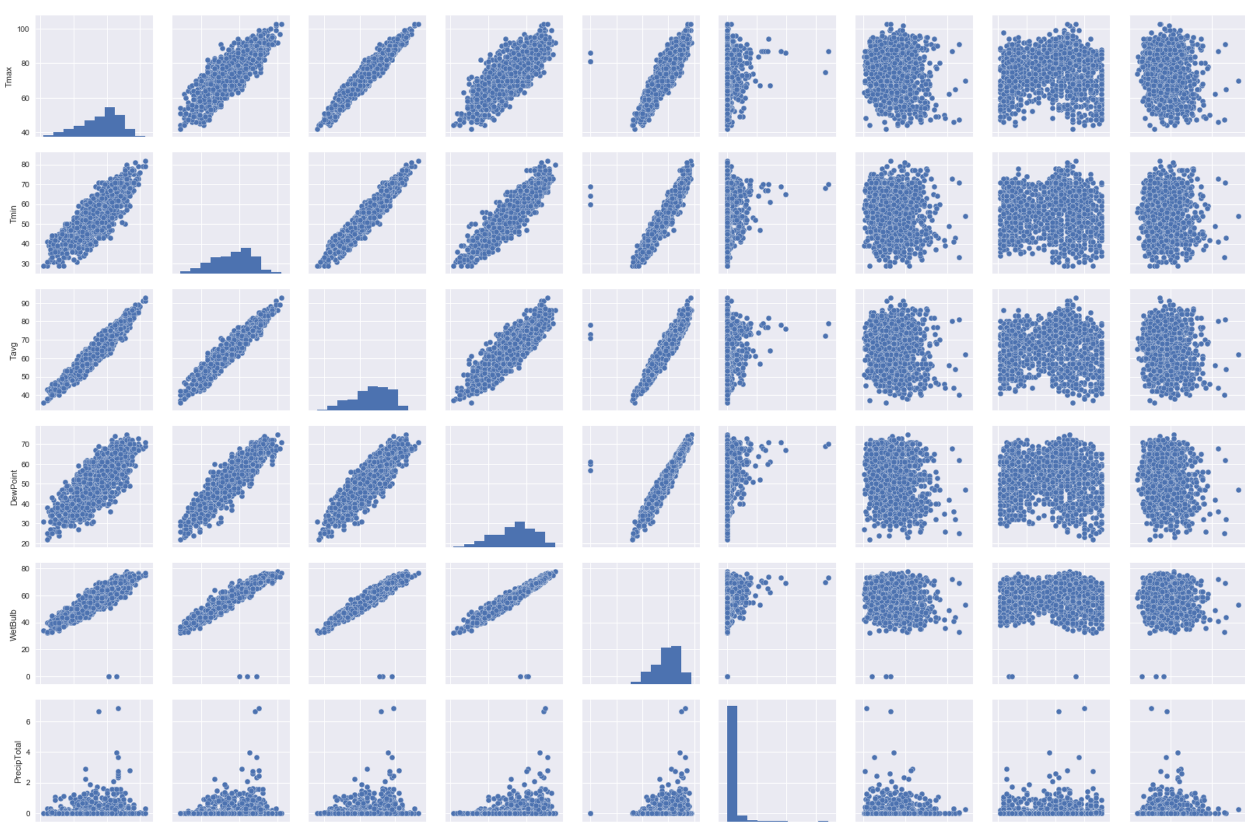
In [14]:
```
sns.pairplot(spray)
```

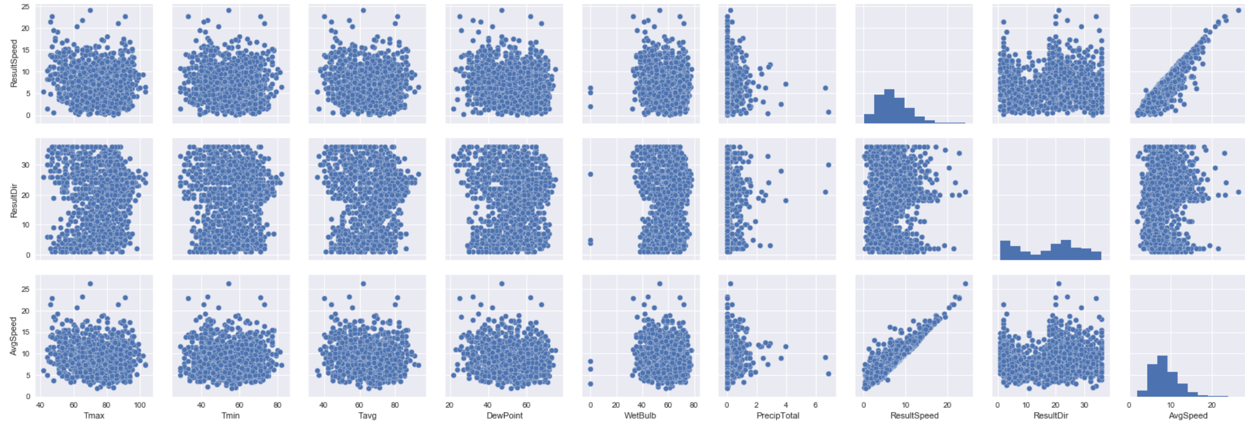
Out[14]: <seaborn.axisgrid.PairGrid at 0x115fa2890>



In [15]:
```
no_dummies = weather.columns.drop(['CodeSum','SeaLevel','StnPressure'])
sns.pairplot(weather[no_dummies])
```

Out[15]: <seaborn.axisgrid.PairGrid at 0x11763be90>

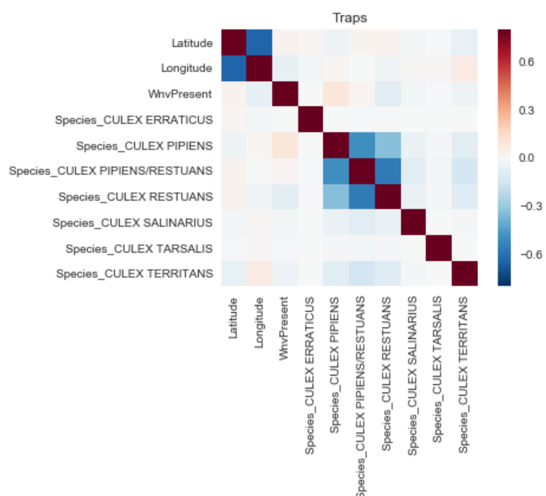




Create More Features

Feature engineering

In [16]:
```
#Before adding anything, let's see what the feature correlation looks like
def find_correlation(data,title):
    correlation = data.corr()
    sns.heatmap(correlation, vmax=.8, square=True)
    plt.title(title)

find_correlation(traps, 'Traps')
```



In [17]:
```
## Parse Dates to see if they can be used in the modeling
traps['year']  = traps['Date'].dt.year
traps['month'] = traps['Date'].dt.month
traps['day']   = traps['Date'].dt.day
```

Add Weather data

This function will add weather features to our traps df, and takes three arguments:

- the column name as a string from weather dataframe that we want to extract
- a numpy function that we want to do to the data
- an integer number of previous days to extract

In [18]:
```
def weather_add(df, weather_col, func, days_range=7):
    new_list = []
    for i in df['Date']:
        mask = (weather['Date'] <= i) & (weather['Date'] >= i - pd.Timedelta(days=days_range))
        data_list = func(weather[weather_col][mask])
        new_list.append(data_list)
    return new_list
```

In [19]:
```
## running this cell will extract the average temp min, average temp max, and precipitation sum
## to the traps dataframe from the previous 7 days, unless otherwise specified

traps['Tmax']    = weather_add(traps, weather_col='Tmax', func=np.mean)
traps['Tmin']    = weather_add(traps, weather_col='Tmin', func=np.mean)
traps['PrecipTotal']    = weather_add(traps, weather_col='PrecipTotal', func= np.sum)
traps['Tmax_3']  = weather_add(traps, weather_col='Tmax', func=np.mean, days_range=3)
traps['Tmax_20'] = weather_add(traps, weather_col='Tmax',func=np.mean, days_range=20)
traps['DewPoint']     = weather_add(traps, weather_col ='DewPoint', func=np.mean, days_range = 10)
traps['Tmin_3']  = weather_add(traps, weather_col='Tmin', func=np.mean, days_range=3)
traps['Tmin_20'] = weather_add(traps, weather_col='Tmin', func=np.mean, days_range=20)

for col in ['Tavg','WetBulb','CodeSum','StnPressure','SeaLevel', 'ResultSpeed', 'ResultDir','AvgSpeed']:
```

```
    traps[col] = weather_add(traps, weather_col=col, func=np.mean)
```

Add Spray data

This function will add spray features to our traps df, and takes 5 arguments:

- dataframe that will be added to
- start: integer number of days from trap inspection (closer to date)
- stop: integer number of days from trap inspection (farther from date)
- col: spray column with the closest distance of spray
- Spray_col: spray column with the number of days since that spray

In [5]:
```
def add_cols(traps,start,stop,col,Spray_col):
    # ex) I want the week leading up to the inspection date: start = 0, end = 7
    # ex) I want the week before that: start = 7, end = 14
    from geopy.distance import vincenty
    traps_sprayed = traps[traps[Spray_col].isnull()].index.values
    remaining = len(traps_sprayed)

    for i in traps_sprayed:
        if start>0: # subtract # of days from the date the trap is inspected
            start_date = traps.Date.loc[i] - pd.Timedelta(days=start)
        else: # if start=0, then we're starting on the trap inspection day and collecting data backwards
            start_date = traps.Date.loc[i]
        end_date = traps.Date.loc[i] - pd.Timedelta(days=stop)
        dates = pd.date_range(start=end_date, end=start_date).tolist() # create list of all dates in our start, end points
        trap_lat = traps.Latitude.loc[i]
        trap_long = traps.Longitude.loc[i]
        dist = []

        # for each dated trap inspection, select only the spray records within the date range
        spray_temp = spray[['Latitude','Longitude','Date']][spray.Date.isin(dates)]

        remaining-=1 # counts how many records are left to process
        print str(remaining),' remaining'

        # run through each coordinate in the spray data and record the distance from our trap
        for j in range(0,len(spray_temp)):
            spray_lat = spray_temp.Latitude.iloc[j]
            spray_long = spray_temp.Longitude.iloc[j]
            a = (trap_lat, trap_long) # trap coordinates
            b = (spray_lat, spray_long) # spray coordinates
            dist.append(vincenty(a, b).miles) # calculate the distance between the points

        try:
            # set the spray value to the shortest distance
            traps[Spray_col].loc[i] = min(dist)
            dt = dist.index(min(dist))
            spray_dt = spray_temp.Date.iloc[dt]
            # record the number of days from inspection that the nearest spray occurred
            traps[col].loc[i] = pd.Timedelta(traps.Date.loc[i]-spray_dt).days
        except:
            pass
```

In [ ]:
```
# get the indicies of trap data that actually have spray data
traps_spray = traps[traps.Year.isin([2011,2013])]

# create the columns
traps_spray['Spray_Dist'] = np.NaN
traps_spray['Spray_Days_Ago'] = np.NaN

# week leading up to inspection
add_cols(traps_spray,0,7,'Spray_Days_Ago','Spray_Dist')
#one week out
add_cols(traps_spray,7,14,'Spray_Days_Ago','Spray_Dist')
# two weeks out
add_cols(traps_spray,14,21,'Spray_Days_Ago','Spray_Dist')
# three weeks out
add_cols(traps_spray,21,28,'Spray_Days_Ago','Spray_Dist')
# four weeks out
add_cols(traps_spray,28,35,'Spray_Days_Ago','Spray_Dist')
```

In [ ]:
```
# Check to see how many values we were able to fill in
traps['Spray'].isnull().sum()/float(len(traps['Spray']))
```

Nope. Not going to include spray data. We could potentially model the spray data from 2011, 2013 to predict values for 2007, 2009 to fill our data, but we didn't have time to go down that path.

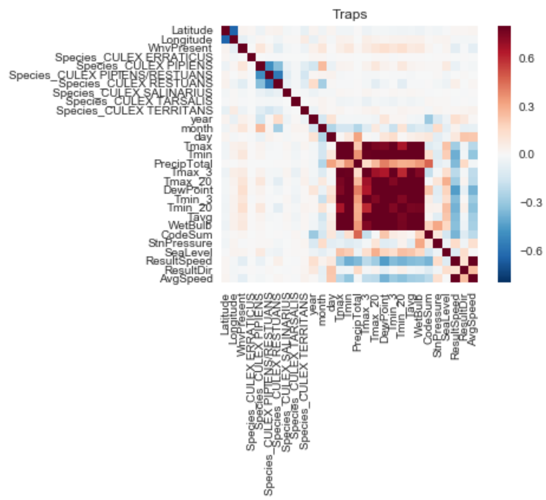
In [ ]:
```
traps.drop(['Spray_Dist','Spray_Days_Ago'],axis=1,inplace=True)
```

In [23]:
```
## Save the transformed tables so we don't have to run the earlier cells
# traps.to_csv('./assets/Train_transformed/traps_jd.csv', encoding='utf-8', index=False)
```

In [2]:
```
##re-import the altered traps file if re-running and want to skip steps above
# traps = pd.read_csv('./assets/Train_transformed/traps_jd.csv')
```

Feature Selection

In [20]:
```
## Check out how the correlation map changed with our new features
find_correlation(traps, 'Traps')
```



In [24]:
```
X.columns
```

Out[24]:
```
Index([u'Latitude', u'Longitude', u'Species_CULEX ERRATICUS',
       u'Species_CULEX PIPIENS', u'Species_CULEX PIPIENS/RESTUANS',
       u'Species_CULEX RESTUANS', u'Species_CULEX SALINARIUS',
       u'Species_CULEX TARSALIS', u'Species_CULEX TERRITANS', u'year',
       u'month', u'day', u'Tmax', u'Tmin', u'PrecipTotal', u'Tmax_3',
       u'Tmax_20', u'DewPoint', u'Tmin_3', u'Tmin_20', u'Tavg', u'WetBulb',
       u'CodeSum', u'StnPressure', u'SeaLevel', u'ResultSpeed', u'ResultDir',
       u'AvgSpeed'],
      dtype='object')
```

In [21]:
```
# Get rid of features that we cannot use
features = traps.columns.drop(['WnvPresent','Date','Trap'])

X = traps[features]
y = traps.WnvPresent
```

In [36]:
```
## slightly adapted from: http://blog.datadive.net/selecting-good-features-part-iv-stability-selection-rfe-and-everything-sid
e-by-side/

# from sklearn.feature_selection import SelectPercentile
from sklearn.linear_model import RandomizedLogisticRegression
from sklearn.feature_selection import RFECV, f_classif
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
import numpy as np

# create a function that scales the data, takes the data
# and scores the features, storing it in a dictionary, ranks
def rank_to_dict(ranks, names, order=1):
    minmax = StandardScaler()
    ranks = minmax.fit_transform(order*np.array([ranks]).T).T[0]
    ranks = map(lambda x: round(x, 2), ranks)
    return dict(zip(names, ranks ))

ranks = {}

lr = RandomizedLogisticRegression()
lr.fit(X, y)
ranks["Logistic"] = rank_to_dict(np.abs(lr.scores_), features)

rf = RandomForestClassifier()
rf.fit(X,y)
ranks["RF"] = rank_to_dict(rf.feature_importances_, features)

f, pval  = f_classif(X, y)
ranks["F_Classif."] = rank_to_dict(f, features)

r = {}
for name in features:
    r[name] = round(np.mean([ranks[method][name] for method in ranks.keys()]), 2)

methods = sorted(ranks.keys())

# average out the scores
ranks["Mean"] = r
methods.append("Mean")


# Now that we have our data, convert to dataframe for better viewing
feats = []
names = []

# feature names
for i in ranks['RF']:
    names.append(i)

feats.append(names)
```

```
# feature importances
for i in ranks:
    row = []
    for j in ranks[i]:
        row.append(ranks[i][j])
    feats.append(row)

feats_t = []

for i in range(0,len(features)):
    row = []
    for f in feats:
        row.append(f[i])
    feats_t.append(row)

feature_importances = pd.DataFrame(feats_t,columns = ['Feature','F_Classif','Logistic','RF','Mean'])
```

In [95]:
```
feature_importances.sort_values(['Mean'],ascending=False)

# feature_importances.sort_values(['Mean','F_Classif','Logistic','RF'],ascending=False)
# feature_importances.Feature
```

Out[95]:

	Feature	F_Classif	Logistic	RF	Mean
18	Longitude	3.59	0.14	1.52	1.75
15	DewPoint	-0.23	2.47	1.99	1.41
5	Tmin_20	-0.28	2.44	1.94	1.37
2	month	-0.27	0.92	2.12	0.92
1	Species_CULEX PIPIENS	-0.07	0.89	1.76	0.86
9	Species_CULEX RESTUANS	-0.14	0.75	1.81	0.81
4	Latitude	3.60	-0.79	-0.63	0.73
10	Tmax_20	-0.26	1.25	0.06	0.35
16	Tmin_3	-0.30	0.90	0.24	0.28
20	ResultSpeed	-0.27	0.54	0.09	0.12
6	Tmin	-0.31	0.72	-0.30	0.04
7	WetBulb	-0.25	0.41	-0.58	-0.14
25	AvgSpeed	-0.32	0.23	-0.48	-0.19
0	Tavg	-0.29	0.16	-0.63	-0.25
26	Tmax_3	-0.31	-0.07	-0.63	-0.34
17	Tmax	-0.34	-0.35	-0.63	-0.44
22	Species_CULEX PIPIENS/RESTUANS	-0.02	-0.91	-0.63	-0.52
3	year	-0.32	-0.62	-0.63	-0.52
8	Species_CULEX TERRITANS	-0.35	-0.69	-0.63	-0.56
27	SeaLevel	-0.24	-0.86	-0.63	-0.58
13	CodeSum	-0.32	-0.87	-0.63	-0.61
12	StnPressure	-0.22	-0.97	-0.63	-0.61
19	Species_CULEX SALINARIUS	-0.36	-0.87	-0.63	-0.62
11	PrecipTotal	-0.32	-0.94	-0.63	-0.63
21	day	-0.32	-0.98	-0.63	-0.64
14	ResultDir	-0.33	-0.96	-0.63	-0.64
23	Species_CULEX TARSALIS	-0.38	-0.97	-0.63	-0.66
24	Species_CULEX ERRATICUS	-0.38	-0.98	-0.63	-0.66

Cutting off the features at Tmin_3--use all above it. Also, this has been re-run several times and somehow the Species_CULEX RESTUANS shot up the ranks. This feature, however, wasn't used in any of our models, so it will not be included.

In [98]:
```
features_new = list(feature_importances.sort_values(['Mean','F_Classif','Logistic','RF'],ascending=False)['Feature'][0:9])
features_new.remove('Species_CULEX RESTUANS')
```

In [103]:
```
X = traps[features_new]
y = traps.WnvPresent
```

Scale the Data

We will use the StandardScaler to scale our data for us in the RandomForest models and SVM models. We'll also just keep the regular data for comparison

In [104]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler, normalize

X_s = pd.DataFrame(StandardScaler().fit_transform(X[X.columns.drop('Species_CULEX PIPIENS')]),columns=X.columns.drop('Species
_CULEX PIPIENS'))
X_s = pd.DataFrame(X['Species_CULEX PIPIENS']).merge(X_s,left_on=X.index.values, right_on=X_s.index.values)
X_s.drop('key_0',inplace=True,axis=1)
```

Train-Test Split

Creating a stratified train-test split to evaluate our models. Stratified because, as noted above, zeroes dominate WnvPositive at 94%.

In [55]:
```
from sklearn.model_selection import train_test_split
```

Split the raw, unscaled data

In [105]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=.33, stratify=y)
```

Split the scaled data

In [106]:
```
X_train_s, X_test_s, y_train_s, y_test_s = train_test_split(X_s,y,train_size=.33, stratify=y)
```

Check that both sets have identical shape

In [107]:
```
print 'Raw splits:'
print X_train.shape, X_test.shape, y_test.shape, y_train.shape
print
print 'Scaled splits:'
print X_train_s.shape, X_test_s.shape, y_test_s.shape, y_train_s.shape
```

```
Raw splits:
(2841, 8) (5769, 8) (5769,) (2841,)

Scaled splits:
(2841, 8) (5769, 8) (5769,) (2841,)
```

Building the Models

Create a function that we will use to evaluate our models. It will return the ROC score that we can use to see how well it will do on Kaggle.

In [48]:
```
from sklearn.metrics import roc_auc_score

def score_model(model,X_test,y_test):
    preds = model.predict_proba(X_test)
    pred_list =[]

    for x in preds:
        pred_list.append(x[1])

    roc_score = roc_auc_score(y_test, pred_list)
    return roc_score
```

(1/6) Random Forest

In [49]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

RF = RandomForestClassifier(n_estimators = 1000,
                            bootstrap=True,
                            max_depth=5,
                            max_features='auto',
                            min_samples_leaf= 1,
                            min_samples_split= 2)
```

Using raw data

In [108]:
```
RF_model= RF.fit(X_train, y_train)
score_model(RF_model,X_test,y_test)
# 0.86780509496634572
```

Out[108]: 0.82547715528947552

Using StandardScaled data

In [109]:
```
RF_model_s = RF.fit(X_train_s, y_train_s)
score_model(RF_model_s,X_test_s, y_test_s)
# 0.81161294220537694
```

Out[109]: 0.82209462587890736

(2/6) Support Vector Machine

In [111]:
```
from sklearn.svm import SVC
```

SVM with kernel = 'rbf'

In [112]:
```
svmc= SVC(probability=True)
svm_model = svmc.fit(X_train,y_train)
```

```
score_model(svm_model,X_test,y_test)
# 0.30215737665155207
```

Out[112]: 0.29652750110966347

In [113]:
```
svm_model_s = svmc.fit(X_train_s,y_train_s)
score_model(svm_model_s,X_test_s,y_test_s)
```

Out[113]: 0.7412381451451775

Scaled data performed significantly better.

Try with the linear kernel by using bagging and ovr

In [114]:
```
# credit: first answer on http://stackoverflow.com/questions/31681373/making-svm-run-faster-in-python

import time
import numpy as np
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
from sklearn import datasets
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC


start = time.time()
clf1 = OneVsRestClassifier(SVC(kernel='linear', probability=True, class_weight='balanced'))
clf1.fit(X_train, y_train)
end = time.time()
print "Single SVC", end - start, clf1.score(X_test,y_test), score_model(clf1,X_test,y_test)

n_estimators = 10
start = time.time()
clf2 = OneVsRestClassifier(BaggingClassifier(SVC(kernel='linear', probability=True, class_weight='balanced'), max_samples=1.0
/ n_estimators, n_estimators=n_estimators))
clf2.fit(X_train, y_train)
end = time.time()
print "Bagging SVC", end - start, clf2.score(X_test,y_test), score_model(clf2,X_test,y_test)


# Single SVC 4.18354606628 0.671693534408 0.754635462093
# Bagging SVC 0.904535055161 0.787831513261 0.746318070825
```

```
Single SVC 3.76783299446 0.655746229849 0.764287440524
Bagging SVC 0.574933052063 0.768070722829 0.752589015349
```

Try with the scaled data

In [115]:
```
# credit: first answer on http://stackoverflow.com/questions/31681373/making-svm-run-faster-in-python

import time
import numpy as np
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
from sklearn import datasets
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC


start = time.time()
clf1s = OneVsRestClassifier(SVC(kernel='linear', probability=True, class_weight='balanced'))
clf1s.fit(X_train_s, y_train_s)
end = time.time()
print "Single SVC", end - start, clf1s.score(X_test_s,y_test_s), score_model(clf1s,X_test_s,y_test_s)

n_estimators = 10
start = time.time()
clf2s = OneVsRestClassifier(BaggingClassifier(SVC(kernel='linear', probability=True, class_weight='balanced'), max_samples=1.
0 / n_estimators, n_estimators=n_estimators))
clf2s.fit(X_train_s, y_train_s)
end = time.time()
print "Bagging SVC", end - start, clf2s.score(X_test_s,y_test_s), score_model(clf2s,X_test_s,y_test_s)


# Single SVC 1.21880817413 0.680013867221 0.751182644026
# Bagging SVC 0.137820005417 0.718495406483 0.744525261444
```

```
Single SVC 1.31022405624 0.648812619171 0.772368542267
Bagging SVC 0.167356967926 0.73565609291 0.762660332911
```

(3/6) Logistic Regression

In [116]:
```
#LOGISTIC REGRESSION
from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
def log(X,y,X_test,y_test):
    # flatten y into a 1-D array
    y_log = np.ravel(y)
    model = LogisticRegression()
    model = model.fit(X, y)
    predicted = model.predict(X_test)
    probs = model.predict_proba(X_test)
    scores = cross_val_score(LogisticRegression(), X, y, scoring='accuracy', cv=10)
    print 'Mean CV score: ' + str(scores.mean())
    print 'Accuracy score: ' + str(metrics.accuracy_score(y_test, predicted))
```

```
    print 'Roc-auc score: ' + str(metrics.roc_auc_score(y_test, probs[:, 1]))
    print ''
    print 'Confusion matrix: \n' + str(metrics.confusion_matrix(y_test, predicted))
    print 'Classification report: \n' + str(metrics.classification_report(y_test, predicted))
    # check the accuracy on the training set
    print 'Model score: ' + str(model.score(X_test, y_test))
    print 'Kaggle: ' + str(score_model(model,X_test,y_test))
    print ''


log(X_train,y_train,X_test,y_test)
log(X_train_s,y_train_s,X_test_s,y_test_s)


# Mean CV score: 0.946850753645
# Accuracy score: 0.946957878315
# Roc-auc score: 0.734609476227

# Mean CV score: 0.946850753645
# Accuracy score: 0.946957878315
# Roc-auc score: 0.761849471011
```

```
Mean CV score: 0.946850753645
Accuracy score: 0.946957878315
Roc-auc score: 0.747154356282

Confusion matrix:
[[5463    0]
 [ 306    0]]
Classification report:
             precision    recall  f1-score   support

          0       0.95      1.00      0.97      5463
          1       0.00      0.00      0.00       306

avg / total       0.90      0.95      0.92      5769

Model score: 0.946957878315
Kaggle: 0.747154356282

Mean CV score: 0.946850753645
Accuracy score: 0.946957878315
Roc-auc score: 0.768921108012

Confusion matrix:
[[5463    0]
 [ 306    0]]
Classification report:
             precision    recall  f1-score   support

          0       0.95      1.00      0.97      5463
          1       0.00      0.00      0.00       306

avg / total       0.90      0.95      0.92      5769

Model score: 0.946957878315
Kaggle: 0.768921108012
```

The logistic regression model using the scaled data looks okay. Making that model and submitting to kaggle.

In [117]:
```
# flatten y into a 1-D array
y_log = np.ravel(y_train_s)
log_model = LogisticRegression()
log_model = log_model.fit(X_train_s, y_train_s)
```

(4/6) ADA Boost

In [118]:
```
from sklearn.ensemble import AdaBoostClassifier
```

In [119]:
```
adaboost= AdaBoostClassifier()
ada_model=adaboost.fit(X,y)
score_model(ada_model,X_test,y_test)
#0.88491183862121936
```

Out[119]: 0.85638831162460716

(5/6) Gradient Boost

In [120]:
```
from sklearn.ensemble import GradientBoostingClassifier

def GradBoostClass(X_train,y_train,X_test,y_test):
    clf = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0,max_depth=1, random_state=0).fit(X_train, y_train)
    clf.score(X_test, y_test)
    print score_model(clf,X_test,y_test)
    print ''

GradBoostClass(X_train,y_train,X_test,y_test)
GradBoostClass(X_train_s,y_train_s,X_test_s,y_test_s)
# 0.807420448196

# 0.799875933045
```

```
0.820344288792
```

```
0.820344288792

0.821106397285
```

In [121]:
```
gradboost = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0,max_depth=1, random_state=0).fit(X_train, y_train)
gradboost.score(X_test, y_test)
```

Out[121]: 0.94661119778124458

(6/6) XG Boost

In [122]:
```
import xgboost as xgb
from xgboost.sklearn import XGBClassifier
import scipy.stats as st

model = XGBClassifier()
xgm = model.fit(X_train, y_train, eval_metric=roc_auc_score)
score_model(xgm,X_test,y_test)
# 0.8723832880791802
```

Out[122]: 0.82574036387390393

6a) XGBoost GridSearch

In [73]:
```
import random

params = {
    "n_estimators": [3,4,5,7,8,10],
    "max_depth": st.randint(3, 40),
    "learning_rate": st.uniform(0.05, 0.4),
    'eval_metric' :'auc',
    'objective': ['binary:logistic']
}

xgbclass = XGBClassifier()
```

In [56]:
```
from sklearn.model_selection import RandomizedSearchCV

gs = GridSearchCV(xgbclass,  params, n_jobs=-1, scoring='roc_auc')
gs.fit(X_train, y_train)

gs.best_estimator_
```

In [123]:
```
xg_grid = XGBClassifier(base_score=0.5, colsample_bylevel=1, colsample_bytree=1,
       gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=3,
       min_child_weight=1, missing=None, n_estimators=100, nthread=-1,
       objective='binary:logistic', reg_alpha=0, reg_lambda=1,
       scale_pos_weight=1, seed=0, silent=True, subsample=1)

xg_final = xg_grid.fit(X_train, y_train)
score_model(xg_final,X_test,y_test)
# 0.81860621483323937
```

Out[123]: 0.82574036387390393

Import and Transform Test Data

In [76]:
```
## Add features
test['Tmax_20'] = weather_add(test, weather_col='Tmax',func=np.mean, days_range=20)
test['DewPoint']= weather_add(test, weather_col ='DewPoint', func=np.mean, days_range = 10)
test['Tmin_3'] = weather_add(test, weather_col='Tmin', func=np.mean, days_range=3)
test['Tmin_20'] = weather_add(test, weather_col='Tmin', func=np.mean, days_range=20)

test['month'] = test['Date'].dt.month
```

In [78]:
```
## Export the tranformed test data to a folder in the repo
## so we don't have to run the above cells every time

# test.to_csv('./assets/Test_transformed/test_transformed_427.csv',sep=',', encoding='utf-8')
```

In [61]:
```
# test = pd.read_csv('./assets/Test_transformed/test_transformed_427.csv')
```

In [81]:
```
test_X = test[features_new]
```

In [82]:
```
test_s = pd.DataFrame(StandardScaler().fit_transform(test_X[test_X.columns.drop(['Species_CULEX PIPIENS'])]),columns=test_X.c
olumns.drop(['Species_CULEX PIPIENS']))
test_s = pd.DataFrame(test_X[['Species_CULEX PIPIENS']]).merge(test_s,left_on=test_X.index.values, right_on=test_s.index.valu
es)
test_s.drop('key_0',inplace=True,axis=1)
```

Exporting to test

In [83]:
```
###This function will takes a model and a model name(as a string), generate predictions,
### and save that as a CSV labeled with the model name and date.
import time
import math
```

```
def model_and_export(model, model_name,test_X=test_X):
    pred_list = []
    predictions =  model.predict_proba(test_X)
    for x in predictions:
        pred_list.append(x[1])
    indexes=np.arange(1, len(predictions)+1, 1)
    preds_df = pd.DataFrame(data=[indexes, pred_list]).T
    preds_df.columns =['Id','WnvPresent']
    preds_df['Id'] = preds_df.Id.astype(int)
    location = './submissions/{}_{}.csv'.format(model_name, time.strftime("%d_%m_%Y"))
    preds_df.to_csv(location, index=False)
    return
```

In [84]:

```
model_and_export(RF_model, 'RF_JD*')
# Your submission scored 0.72874
```

In [85]:

```
model_and_export(log_model, 'LOG_JD*',test_s)
# Your submission scored 0.72305
```

In [86]:

```
model_and_export(clf2s, 'SVM_S*', test_s)
# Your submission scored 0.69906.
```

In [87]:

```
model_and_export(ada_model, 'ADABoost_JD*')
# Your submission scored 0.74416.
```

In [88]:

```
model_and_export(gradboost, 'GRADBOOST_*')
# Your submission scored 0.64589
```

In [89]:

```
model_and_export(xgm, 'XG_JD*')
# Your submission scored 0.75110
```

In [90]:

```
model_and_export(xg_final, 'XG_FINAL*')
# Your submission scored 0.71567
```

Ensembles

In [ ]:

```
def ensemble_and_export(model1,model2,test_X,file_name):
    pred_m1 = []
    predictions_m1 =  model1.predict_proba(test_X)
    pred_m2 = []
    predictions_m2 =  model2.predict_proba(test_X)

    for x in predictions_m1:
        pred_m1.append(x[1])

    for x in predictions_m2:
        pred_m2.append(x[1])

    indexes=np.arange(1, len(predictions_m1)+1, 1)

    preds_m1 = pd.DataFrame(data=[indexes, pred_m1]).T
    preds_m1.columns =['Id','WnvPresent']
    preds_m1['Id'] = preds_m1.Id.astype(int)

    preds_m2 = pd.DataFrame(data=[indexes, pred_m2]).T
    preds_m2.columns =['Id','WnvPresent']
    preds_m2['Id'] = preds_m2.Id.astype(int)

    ensemble = preds_m1.merge(preds_m2,left_on='Id', right_on='Id')

    ensemble['avg'] = (ensemble['WnvPresent_x']+ ensemble['WnvPresent_y']) / 2
```