1 Project 7

In this project, you will implement the the clustering techniques that you've learned this week.

1.0.0.1 Step 1: Load the python libraries that you will need for this project

In [77]:
```
import pandas as pd
import numpy as np
import scipy
from sklearn import preprocessing, decomposition

import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns

import psycopg2 as psy
import sqlalchemy

%matplotlib inline
```

Last executed 2016-11-06 22:14:13 in 783ms

In [2]:
```
plt.style.use("fivethirtyeight")
```

Last executed 2016-11-06 21:44:57 in 5ms

In [3]:
```
%load_ext sql
```

Last executed 2016-11-06 21:44:58 in 569ms

1.0.0.2 Step 2: Examine your data

In [4]:
```
airports = pd.read_csv("../assets/airports.csv")
```

Last executed 2016-11-06 21:44:59 in 212ms

In [5]:
```
airports.columns = [i.replace("_", " ").lower().replace(" ", "_") for i i
```

Last executed 2016-11-06 21:45:00 in 5ms

In [6]:
```
airports.info()
```

Last executed 2016-11-06 21:45:01 in 171ms

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5167 entries, 0 to 5166
Data columns (total 13 columns):
key                         5164 non-null float64
locid                       5152 non-null object
ap_name                     5164 non-null object
alias                       3498 non-null object
facility_type               5164 non-null object
faa_region                  5164 non-null object
county                      5164 non-null object
city                        5164 non-null object
state                       5164 non-null object
ap_type                     5164 non-null object
latitude                    5164 non-null float64
longitude                   5164 non-null float64
boundary_data_available     5164 non-null object
dtypes: float64(3), object(10)
memory usage: 524.8+ KB
```

In [7]:
```
airports.head()
```

Last executed 2016-11-06 21:45:01 in 115ms

Out[7]:

	key	locid	ap_name	alias	facility_type	faa_region	county	city
0	3443.0	STX	HENRY E ROHLSEN	Henry E Rohlsen Int'l Airport	Airport	ASO	-VIRGIN ISLANDS-	CHRIS
1	5088.0	X64	PATILLAS	NaN	Airport	ASO	#NAME?	PATILL
2	2886.0	PSE	MERCEDITA	Aeropuerto Mercedita	Airport	ASO	#NAME?	PONC
3	2879.0	VQS	ANTONIO RIVERA RODRIGUEZ	Aeropuerto Antonio Rivera Rodr&#xfffd;guez	Airport	ASO	#NAME?	ISLA D VIEQU
4	2883.0	X63	HUMACAO	Aeropuerto Regional De Humacao	Airport	ASO	#NAME?	HUMA

In [8]:
```
cancellations = pd.read_csv("../assets/airport_cancellations.csv")
```

Last executed 2016-11-06 21:45:02 in 19ms

In [9]:
```
cancellations.columns = [i.replace("_", " ").lower().replace(" ", "_") fo
```

Last executed 2016-11-06 21:45:02 in 7ms

In [10]:
```
cancellations.info()
```

Last executed 2016-11-06 21:45:03 in 14ms

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 805 entries, 0 to 804
Data columns (total 6 columns):
airport                    805 non-null object
year                       805 non-null float64
departure_cancellations    805 non-null float64
arrival_cancellations      805 non-null float64
departure_diversions       805 non-null float64
arrival_diversions         805 non-null float64
dtypes: float64(5), object(1)
memory usage: 37.8+ KB
```

In [11]:
```
cancellations.head()
```

Last executed 2016-11-06 21:45:03 in 115ms

Out[11]:

	airport	year	departure_cancellations	arrival_cancellations	departure_diversions	arr
0	ABQ	2004.0	242.0	235.0	71.0	46.
1	ABQ	2005.0	221.0	190.0	61.0	33.
2	ABQ	2006.0	392.0	329.0	71.0	12
3	ABQ	2007.0	366.0	304.0	107.0	45.
4	ABQ	2008.0	333.0	300.0	79.0	42.

In [12]:
```
operations = pd.read_csv("../assets/Airport_operations.csv")
```

Last executed 2016-11-06 21:45:04 in 21ms

In [13]:
```
operations.columns = [i.replace("_", " ").replace("-"," ").lower().replac
```

Last executed 2016-11-06 21:45:04 in 6ms

In [14]:
```
operations.info()
```

Last executed 2016-11-06 21:45:05 in 16ms

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 841 entries, 0 to 840
Data columns (total 15 columns):
airport                                 841 non-null object
year                                    841 non-null int64
departures_for_metric_computation       841 non-null int64
arrivals_for_metric_computation         841 non-null int64
percent_on_time_gate_departures         841 non-null float64
percent_on_time_airport_departures      841 non-null float64
percent_on_time_gate_arrivals           841 non-null float64
average_gate_departure_delay            841 non-null float64
average_taxi_out_time                   841 non-null float64
average_taxi_out_delay                  841 non-null float64
average_airport_departure_delay         841 non-null float64
average_airborne_delay                  841 non-null float64
average_taxi_in_delay                   841 non-null float64
average_block_delay                     841 non-null float64
average_gate_arrival_delay              841 non-null float64
dtypes: float64(11), int64(3), object(1)
memory usage: 98.6+ KB
```

In [15]:
```
operations.head()
```

Last executed 2016-11-06 21:45:06 in 81ms

Out[15]:

	airport	year	departures_for_metric_computation	arrivals_for_metric_computation	per
0	ABQ	2004	53971	53818	0.8
1	ABQ	2005	51829	51877	0.8
2	ABQ	2006	49682	51199	0.7
3	ABQ	2007	53255	53611	0.8
4	ABQ	2008	49589	49512	0.8

1.0.1 Intro: Write a problem statement / aim for this project

> The FAA wants to cut down on delays nationwide, and the most important part of this task
> dataset of departure and operational delays.
>
> Objective: Your task is to understand the distribution, characteristics, and components of

1.0.2 Part 1: Create a PostgreSQL database

1.0.2.1 1. Let's create a database where we can house our airport data

In [ ]:
```
# the speeddating database was created in terminal with "CREATE DATABASE
# use %sql magic to connect to the database
# %sql dialect+driver://username:password@host:port/database
%sql postgresql://joce@localhost:5432/airports
```

In [ ]:
```
# check what tables are available in our database right now
```
Last executed 2016-11-06 21:45:08 in 2.36s

In [ ]:
```
%%sql
SELECT table_name
FROM information_schema.tables
WHERE table_schema LIKE 'public';
```
Last executed 2016-11-06 21:45:09 in 1.36s

In [ ]:
```
# to use the pandas.to_sql function, create a connection to the database
engine = sqlalchemy.create_engine("postgresql://joce@localhost:5432/airpo
```
Last executed 2016-11-06 21:45:09 in 1.03s

Load our csv files into tables

In [ ]:
```
airports.to_sql("airports", con=engine, if_exists="replace")
```
Last executed 2016-11-06 21:45:10 in 618ms

In [ ]:
```
%%sql
SELECT * FROM airports LIMIT 3;
```
Last executed 2016-11-06 21:45:10 in 402ms

In [ ]:
```
cancellations.to_sql("cancellations", con=engine, if_exists="replace")
```
Last executed 2016-11-06 21:45:10 in 190ms

In [ ]:
```
%%sql
SELECT * FROM cancellations LIMIT 3;
```

In [ ]:
```
operations.to_sql("operations", con=engine, if_exists="replace")
```

In [ ]:
```
%%sql
SELECT * FROM operations LIMIT 3;
```

Join airport_cancellations.csv and airports.csv into one table

In [40]:
```
a_and_c = cancellations.merge(airports, left_on="airport", right_on="loci
```
Last executed 2016-11-06 21:46:07 in 38ms

In [41]:
```
a_and_c.head(3)
```
Last executed 2016-11-06 21:46:07 in 143ms

Out[41]:

	airport	year	departure_cancellations	arrival_cancellations	departure_diversions	arr
0	ABQ	2004.0	242.0	235.0	71.0	46.
1	ABQ	2005.0	221.0	190.0	61.0	33.
2	ABQ	2006.0	392.0	329.0	71.0	12.

In [42]:
```
a_and_o = operations.merge(airports, left_on="airport", right_on="locid")
```
Last executed 2016-11-06 21:46:07 in 26ms

In [43]:
```
a_and_o.head(3)
```
Last executed 2016-11-06 21:46:07 in 108ms

Out[43]:

	airport	year	departures_for_metric_computation	arrivals_for_metric_computation	per
0	ABQ	2004	53971	53818	0.8
1	ABQ	2005	51829	51877	0.8
2	ABQ	2006	49682	51199	0.7

3 rows × 28 columns

Query the database for our intial data

In [ ]:
```
%%sql
SELECT COUNT(DISTINCT locid)
FROM airports;
```

In [ ]:
```
%%sql
SELECT COUNT(DISTINCT airport)
FROM cancellations;
```
Last executed 2016-11-06 21:45:12 in 10ms

In [ ]:
```
%%sql
SELECT COUNT(DISTINCT airport)
FROM operations;
```

In [44]:
```
df = a_and_o.copy()
```
Last executed 2016-11-06 21:46:11 in 6ms

In [45]:
```
df.info()
```

Last executed 2016-11-06 21:46:12 in 16ms

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 841 entries, 0 to 840
Data columns (total 28 columns):
airport                                 841 non-null object
year                                    841 non-null int64
departures_for_metric_computation       841 non-null int64
arrivals_for_metric_computation         841 non-null int64
percent_on_time_gate_departures         841 non-null float64
percent_on_time_airport_departures      841 non-null float64
percent_on_time_gate_arrivals           841 non-null float64
average_gate_departure_delay            841 non-null float64
average_taxi_out_time                   841 non-null float64
average_taxi_out_delay                  841 non-null float64
average_airport_departure_delay         841 non-null float64
average_airborne_delay                  841 non-null float64
average_taxi_in_delay                   841 non-null float64
average_block_delay                     841 non-null float64
average_gate_arrival_delay              841 non-null float64
key                                     841 non-null float64
locid                                   841 non-null object
ap_name                                 841 non-null object
alias                                   841 non-null object
facility_type                           841 non-null object
faa_region                              841 non-null object
county                                  841 non-null object
city                                    841 non-null object
state                                   841 non-null object
ap_type                                 841 non-null object
latitude                                841 non-null float64
longitude                               841 non-null float64
boundary_data_available                 841 non-null object
dtypes: float64(14), int64(3), object(11)
memory usage: 190.5+ KB
```

1.0.2.2 1.2 What are the risks and assumptions of our data?

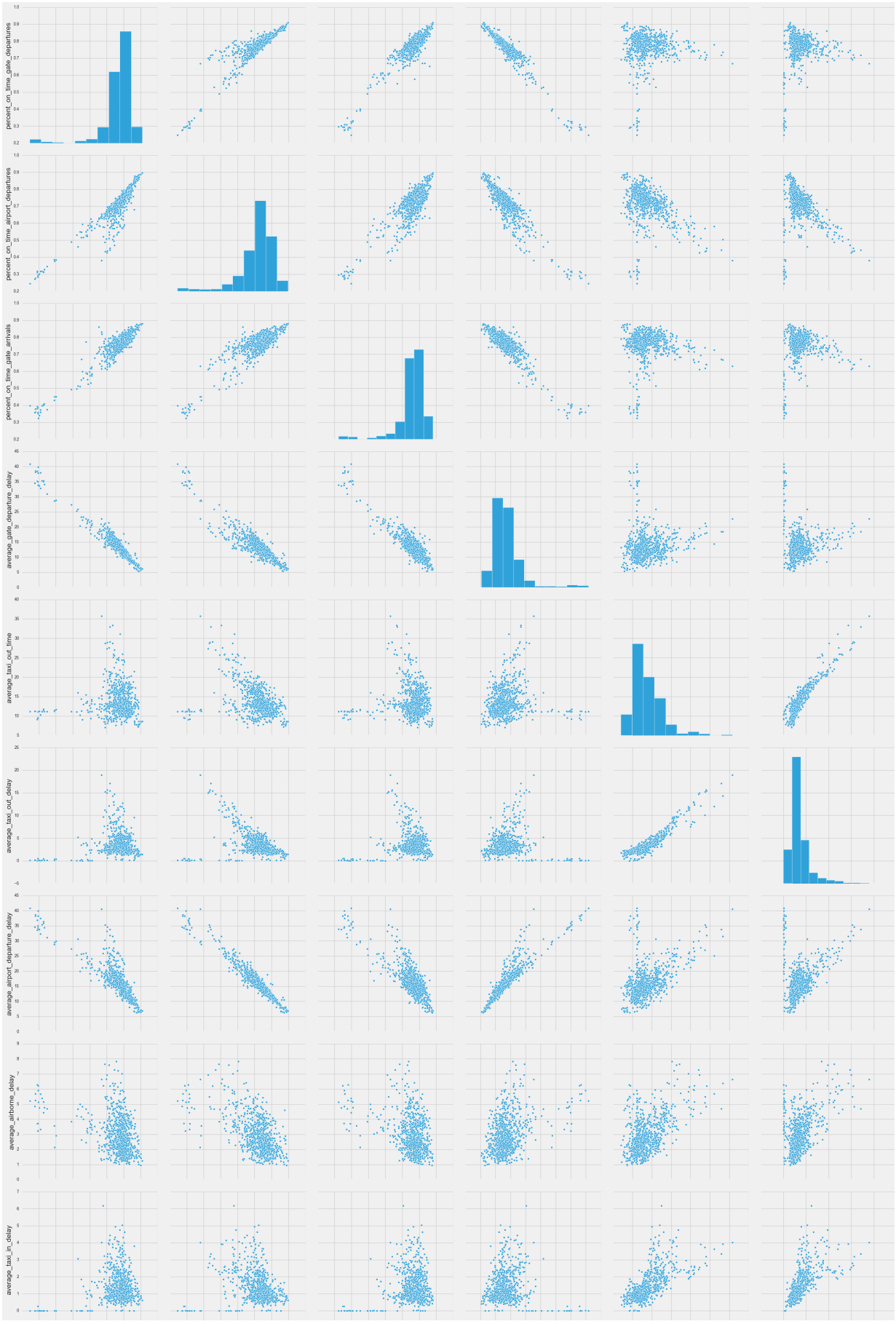
- Our data is only available by the year
  - Assumption: The time of the year/ seasons/ time of the day do not have any effect on del
- Out of 5152 airports, we only have cancellation data for 74 airports and operations delay data
  - Assumption: The airports that we have data for is representative of all the airports
- We don't have airline data
  - Assumption: The airline does not have any effect on delays or cancellations

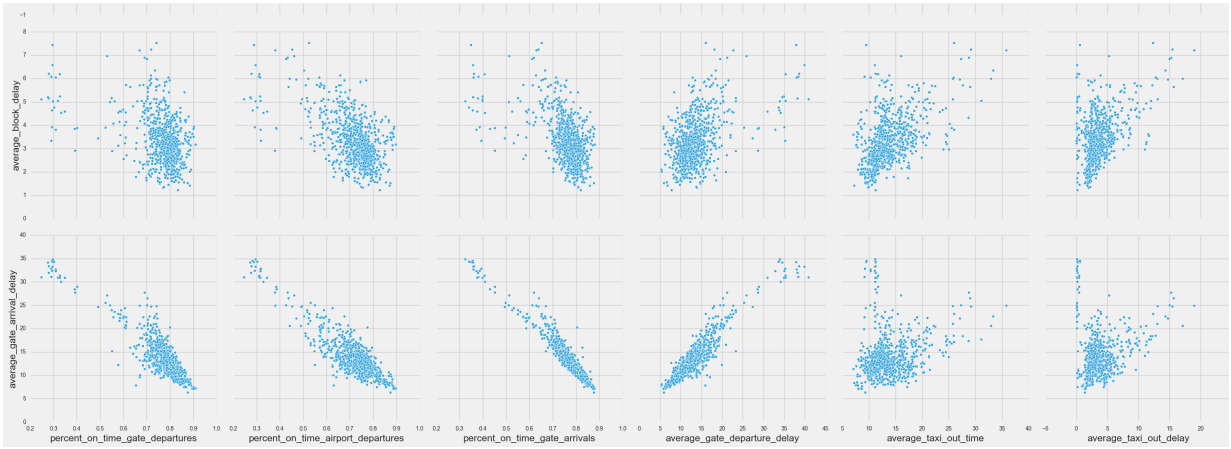
1.0.3 Part 2: Exploratory Data Analysis

1.0.3.1 2.1 Plot and Describe the Data

In [46]:
```
sns.pairplot(df[[i for i in df.columns if "average" in i or "percent" in
plt.xticks(fontsize=5);
```

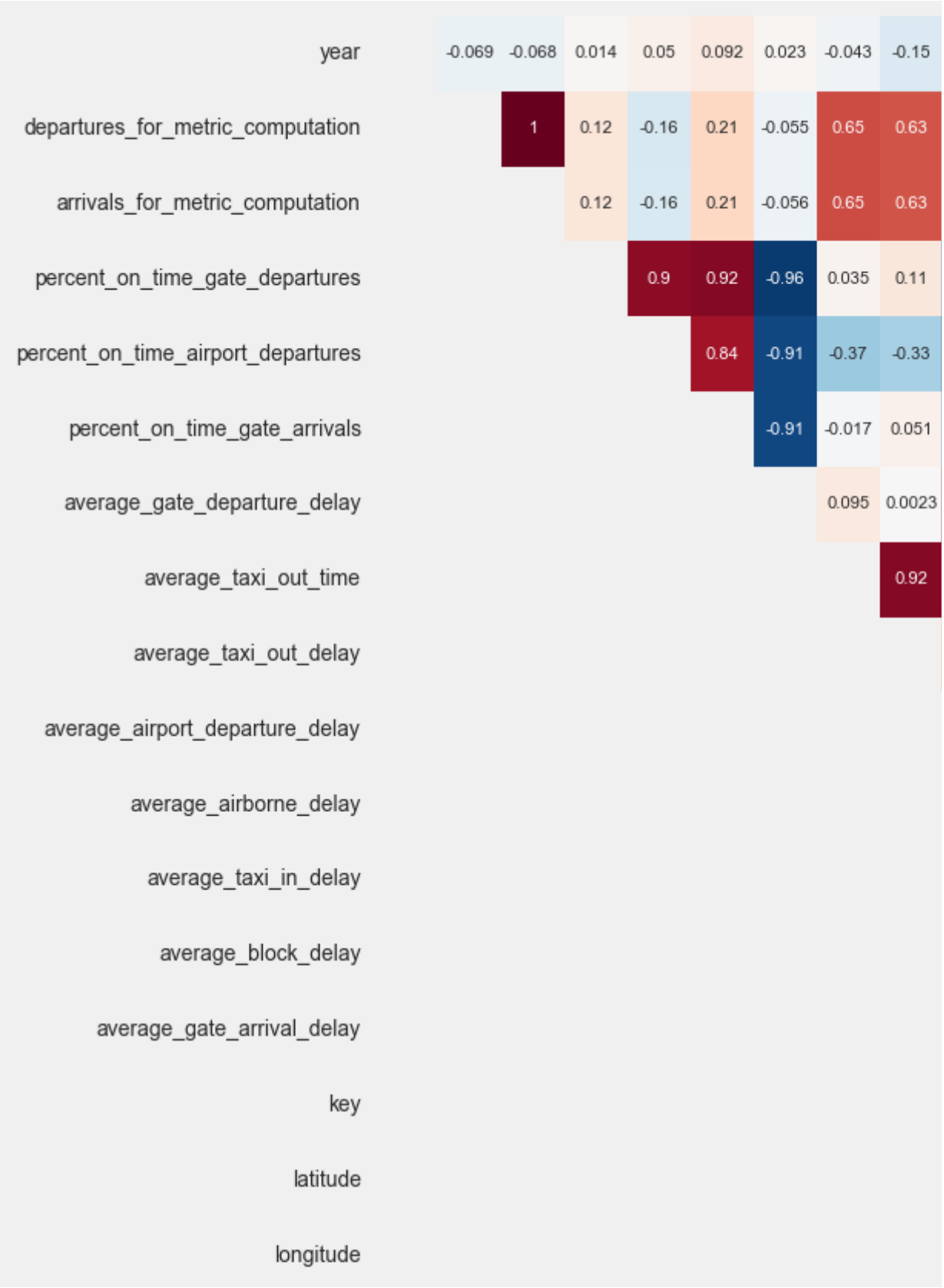
Last executed 2016-11-06 21:46:14 in 39.8s




average_block_delay
average_gate_arrival_delay
percent_on_time_gate_departures
percent_on_time_airport_departures
percent_on_time_gate_arrivals
average_gate_departure_delay
average_taxi_out_time
average_taxi_out_delay

In [47]:
```
# create a mask so that only one half of our heatmap shows up
# this takes out duplicates in the grid and also the spots where a variab
mask = np.zeros_like(df.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
plt.subplots(figsize=(10,10));
sns.heatmap(df.corr(), mask=mask.T, annot=True, annot_kws={"fontsize": 8}
```

Last executed 2016-11-06 21:46:53 in 2.56s



year

departures_for_metric_computation

arrivals_for_metric_computation

percent_on_time_gate_departures

percent_on_time_airport_departures

percent_on_time_gate_arrivals

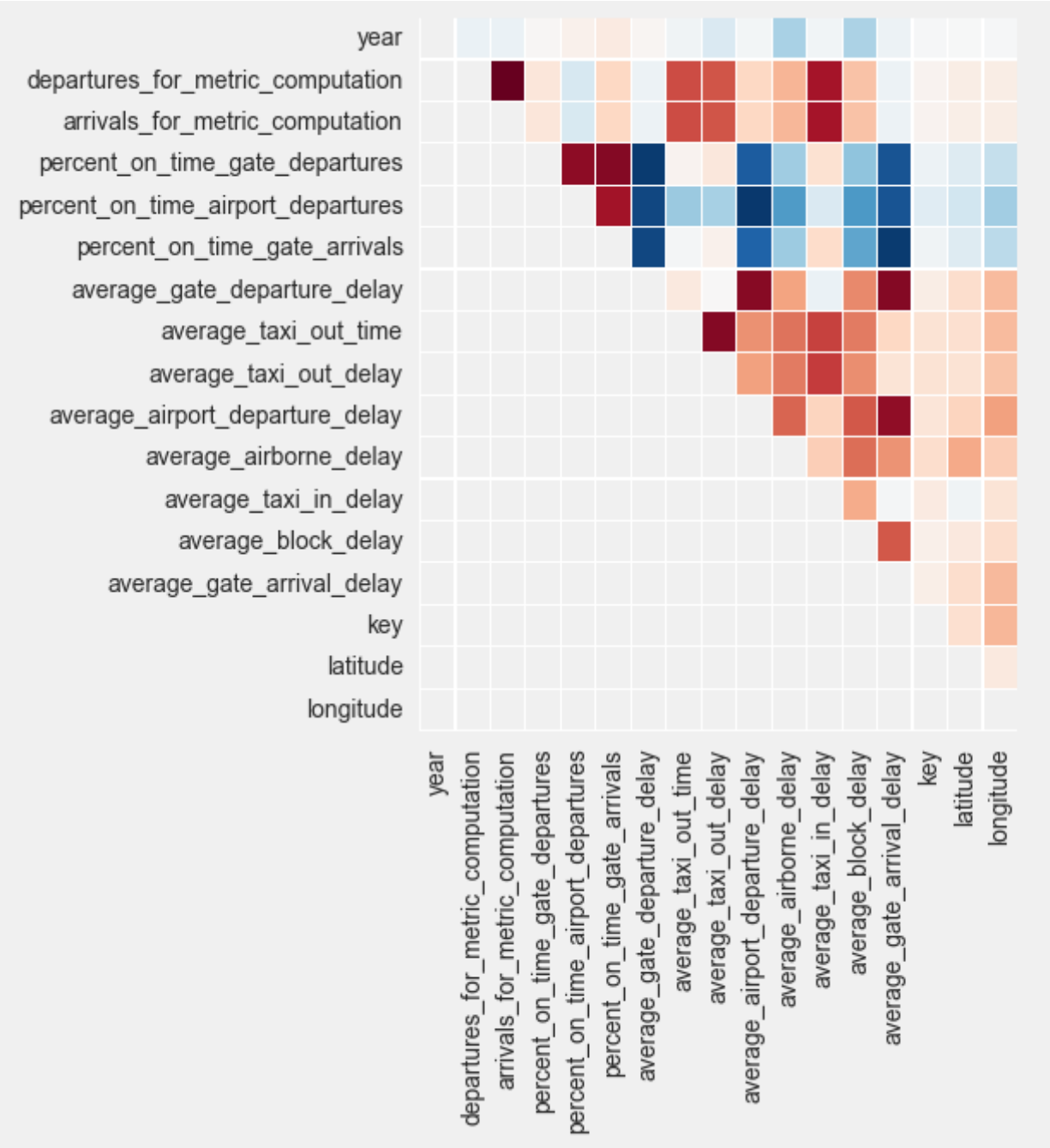
average_gate_departure_delay

average_taxi_out_time

average_taxi_out_delay

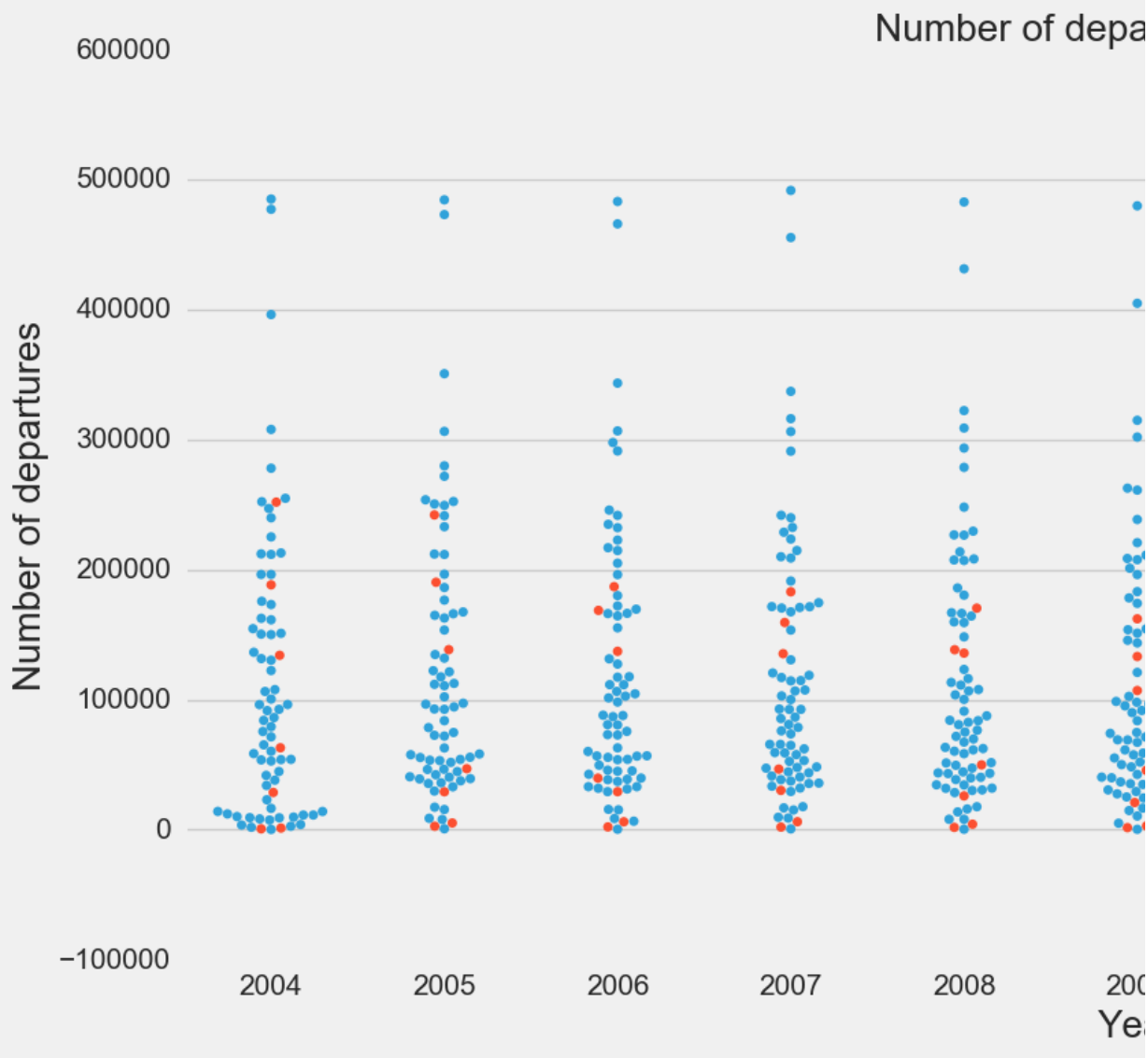
In [48]:
```
# create a mask so that only one half of our heatmap shows up
# this takes out duplicates in the grid and also the spots where a variab
mask = np.zeros_like(df.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
plt.subplots(figsize=(5,5));
sns.heatmap(df.corr(), mask=mask.T, linewidths=0.1);
```

Last executed 2016-11-06 21:46:56 in 1.28s



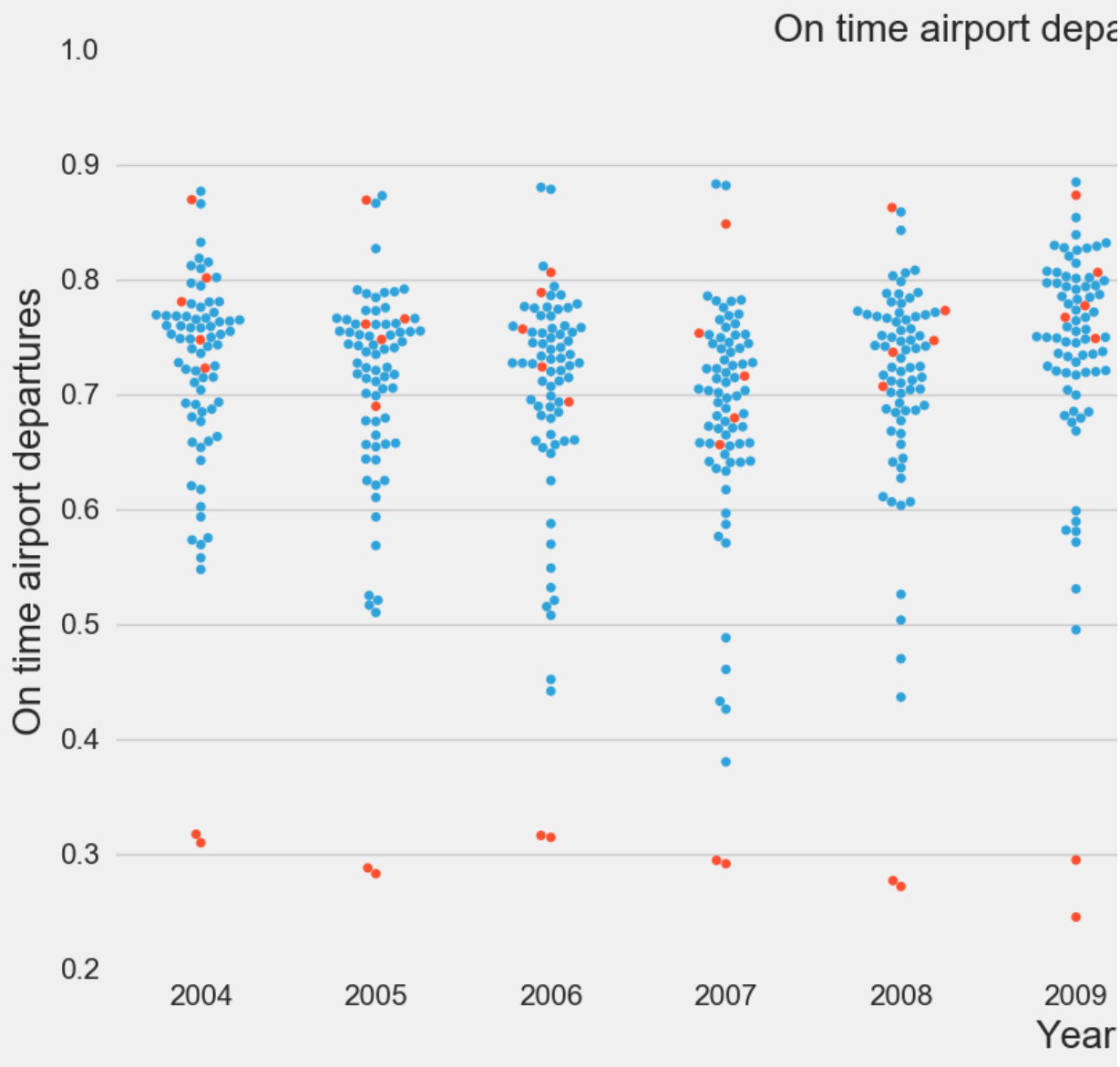
In [49]:
```
# number of departures
plt.subplots(figsize=(16,8));
ax = sns.swarmplot(y="departures_for_metric_computation", x="year", hue="
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("Number of departures", fontsize=20);
plt.xlabel("Year", fontsize=20);
plt.title("Number of departures per year");
```

Last executed 2016-11-06 21:46:57 in 2.10s



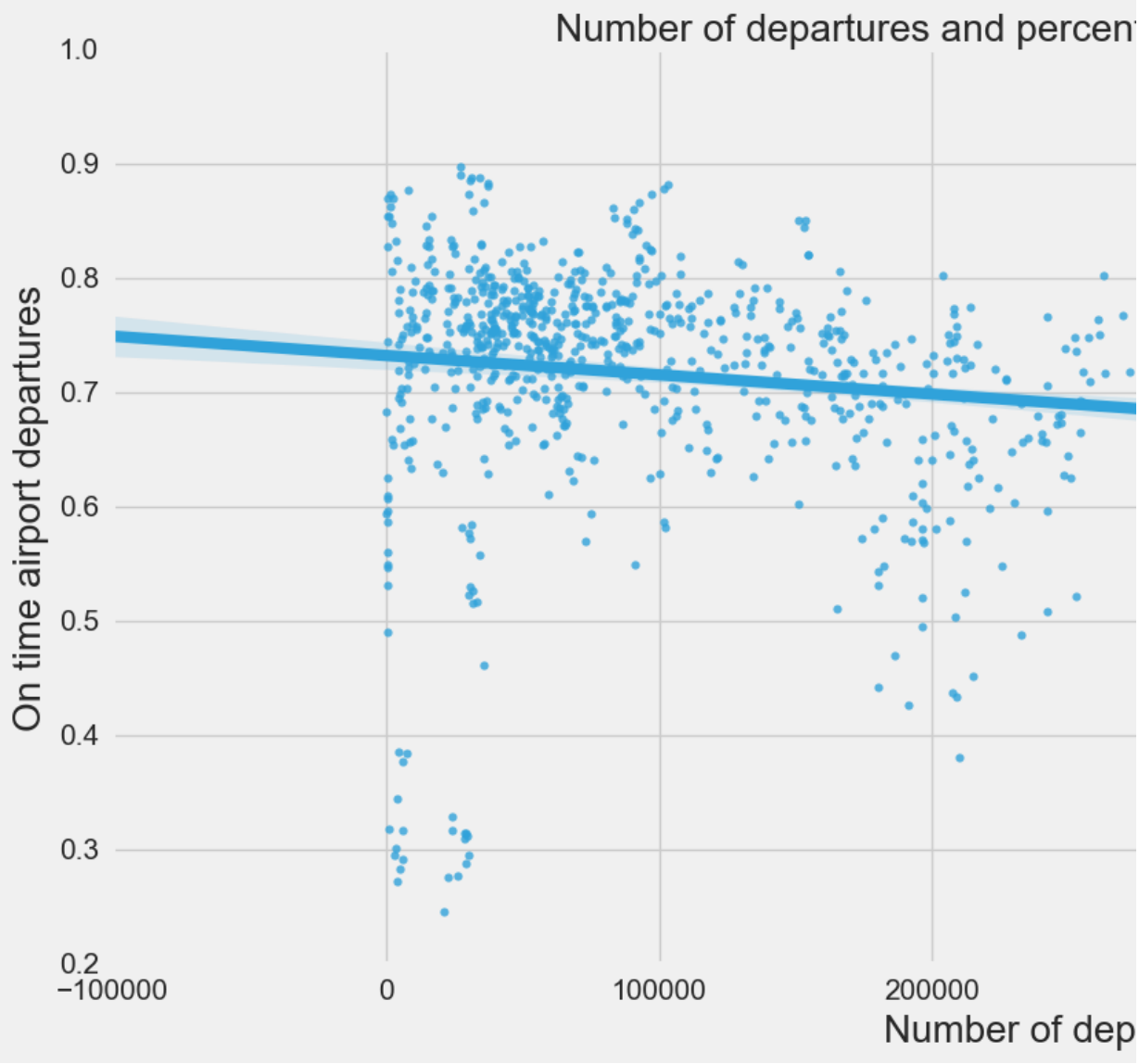
In [50]:
```
# percentage of on time departures
plt.subplots(figsize=(16,8));
sns.swarmplot(y="percent_on_time_airport_departures", x="year", hue="ap_t
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("On time airport departures", fontsize=20);
plt.xlabel("Year", fontsize=20);
plt.title("On time airport departures per year");
```

Last executed 2016-11-06 21:46:59 in 1.99s



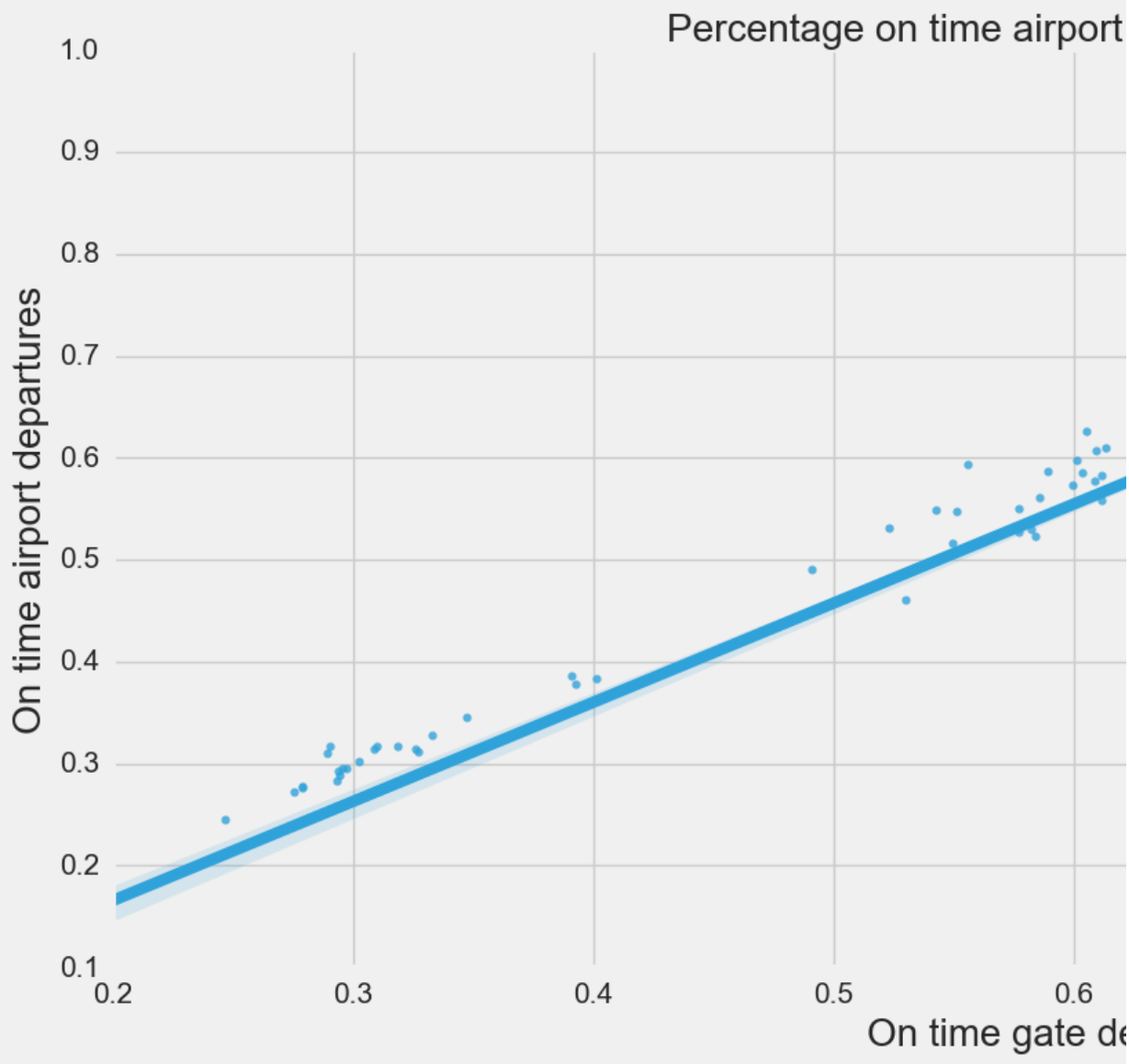
In [51]:
```
# percentage of on time departures
plt.subplots(figsize=(16,8));
sns.regplot(y="percent_on_time_airport_departures", x="departures_for_met
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("On time airport departures", fontsize=20);
plt.xlabel("Number of departures", fontsize=20);
plt.title("Number of departures and percentage of on time departures");
```

Last executed 2016-11-06 21:47:01 in 2.69s



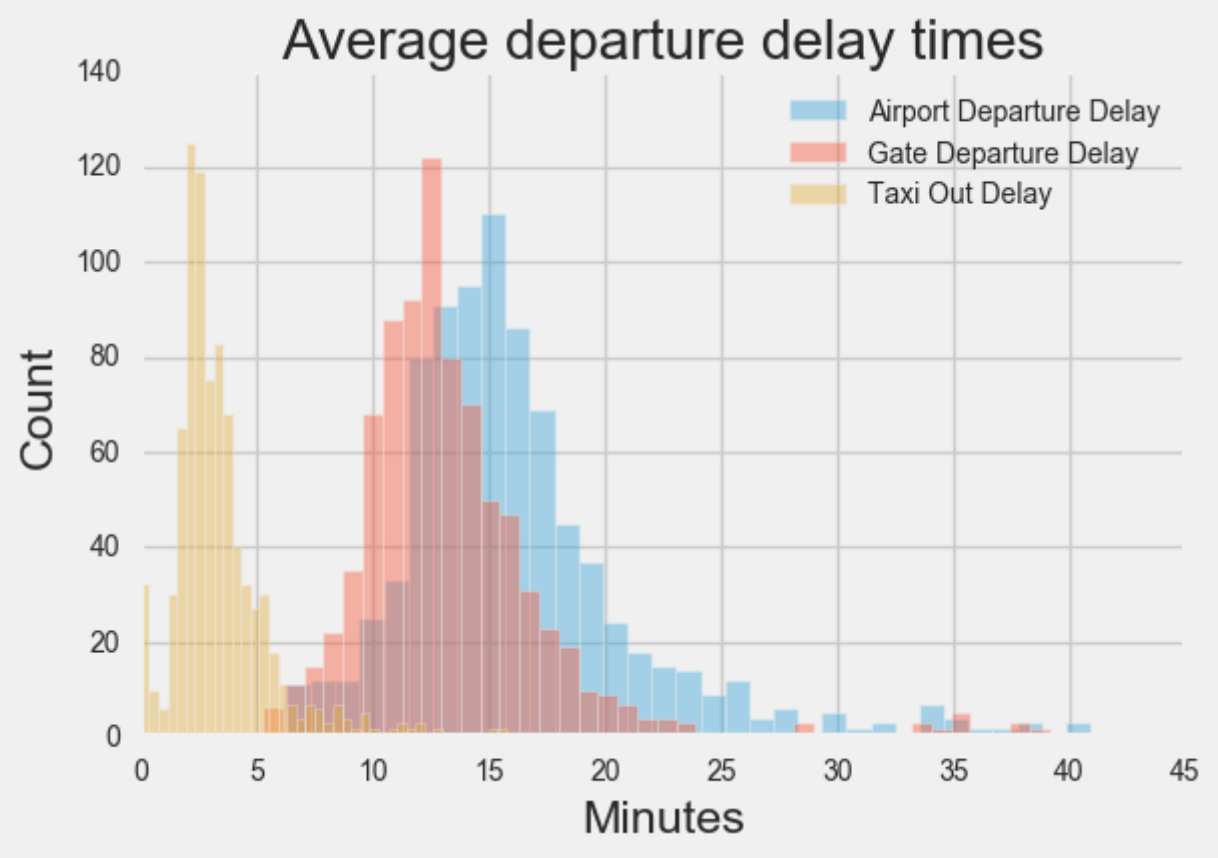
In [52]:
```
# percentage of on time departures vs percentage of on time gate departur
plt.subplots(figsize=(16,8));
sns.regplot(y="percent_on_time_airport_departures", x="percent_on_time_ga
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("On time airport departures", fontsize=20);
plt.xlabel("On time gate departures", fontsize=20);
plt.title("Percentage on time airport and gate departures");
```

Last executed 2016-11-06 21:47:04 in 2.10s



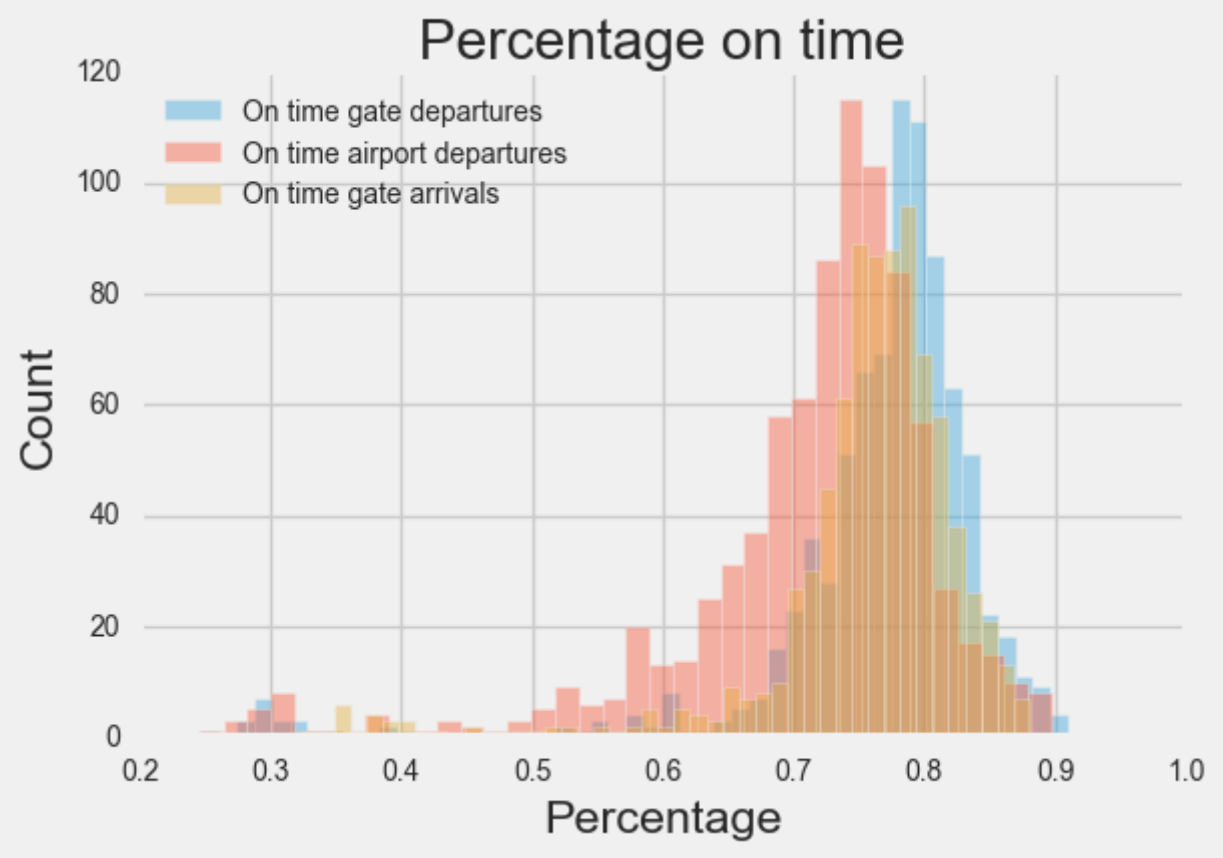
In [53]:
```
sns.distplot(df["average_airport_departure_delay"], kde=False, label="Air
sns.distplot(df["average_gate_departure_delay"], kde=False, label="Gate D
sns.distplot(df["average_taxi_out_delay"], kde=False, label="Taxi Out Del
plt.legend(loc="best");
plt.title("Average departure delay times");
plt.ylabel("Count");
plt.xlabel("Minutes");
```

Last executed 2016-11-06 21:47:06 in 1.19s



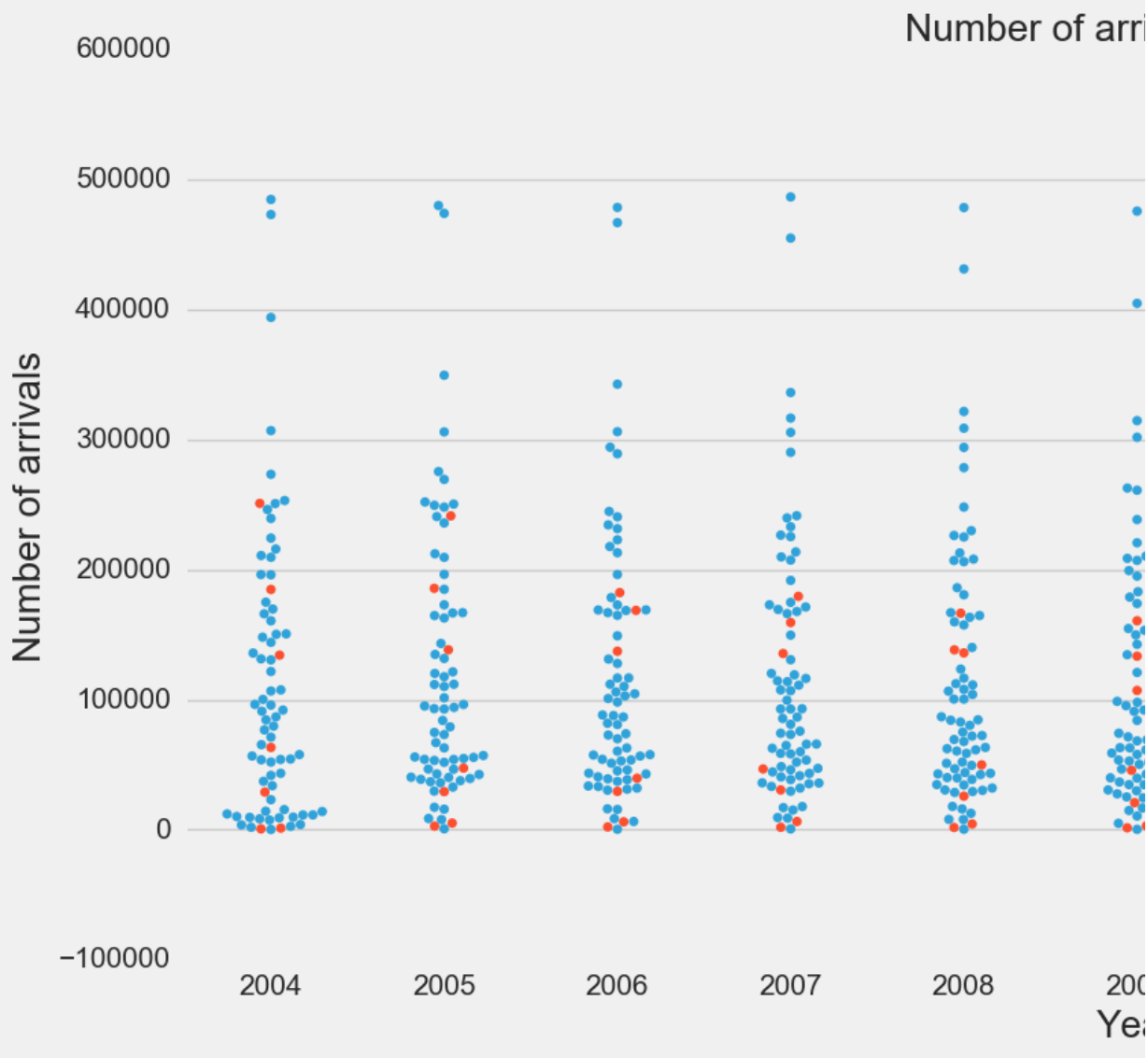
In [67]:
```
sns.distplot(df["percent_on_time_gate_departures"], kde=False, label="On
sns.distplot(df["percent_on_time_airport_departures"], kde=False, label="
sns.distplot(df["percent_on_time_gate_arrivals"], kde=False, label="On ti
plt.legend(loc="best");
plt.title("Percentage on time");
plt.ylabel("Count");
plt.xlabel("Percentage");
```

Last executed 2016-11-06 21:58:57 in 862ms



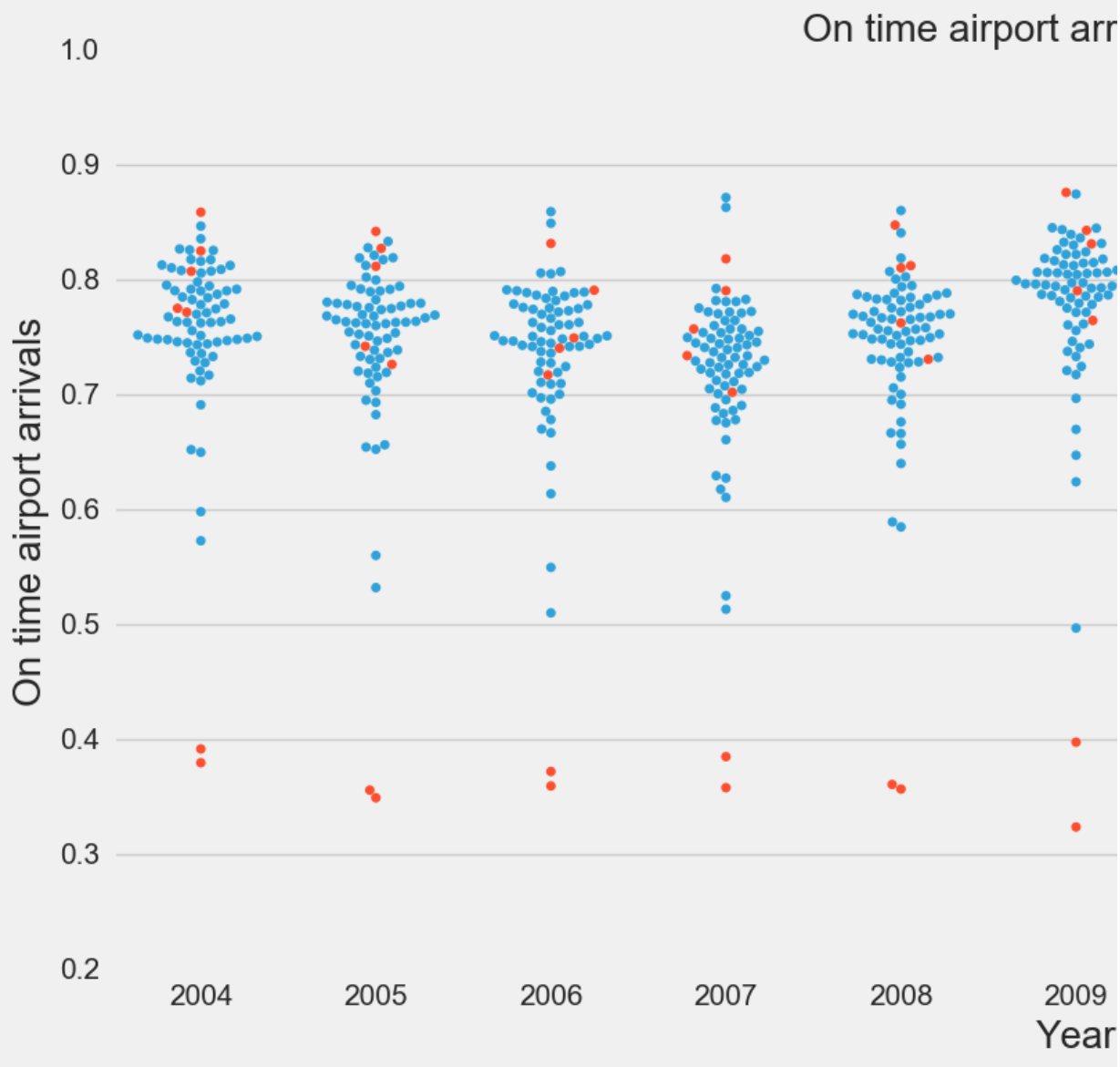
In [54]:
```
# number of arrivals
plt.subplots(figsize=(16,8));
ax = sns.swarmplot(y="arrivals_for_metric_computation", x="year", hue="ap
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("Number of arrivals", fontsize=20);
plt.xlabel("Year", fontsize=20);
plt.title("Number of arrivals per year");
```

Last executed 2016-11-06 21:47:07 in 1.99s



In [65]:
```
# percentage of on time departures
plt.subplots(figsize=(16,8));
sns.swarmplot(y="percent_on_time_gate_arrivals", x="year", hue="ap_type",
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("On time airport arrivals", fontsize=20);
plt.xlabel("Year", fontsize=20);
plt.title("On time airport arrivals per year");
```

Last executed 2016-11-06 21:55:54 in 1.34s

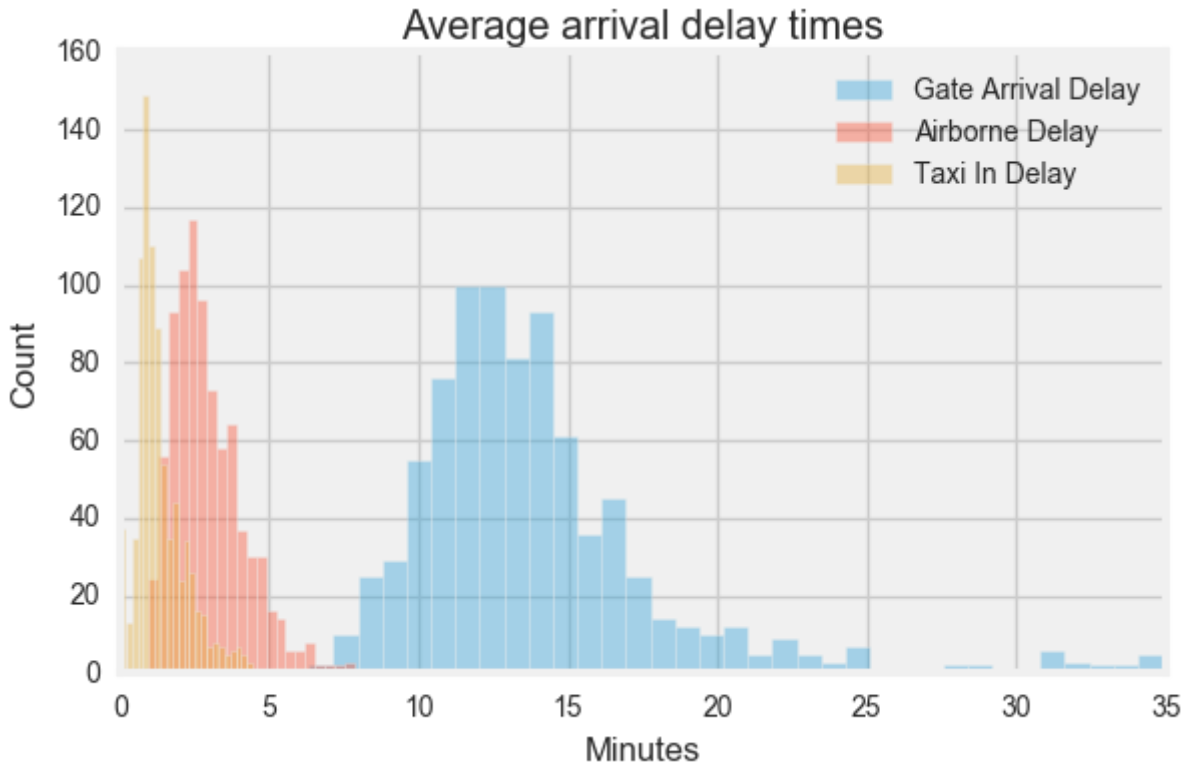


In [55]:
```
# percentage of on time arrivals
plt.subplots(figsize=(16,8));
sns.regplot(y="percent_on_time_gate_arrivals", x="arrivals_for_metric_com
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("On time airport arrivals", fontsize=20);
plt.xlabel("Number of arrivals", fontsize=20);
plt.title("Number of arrivals and percentage of on time arrivals");
```

Last executed 2016-11-06 21:47:09 in 1.39s

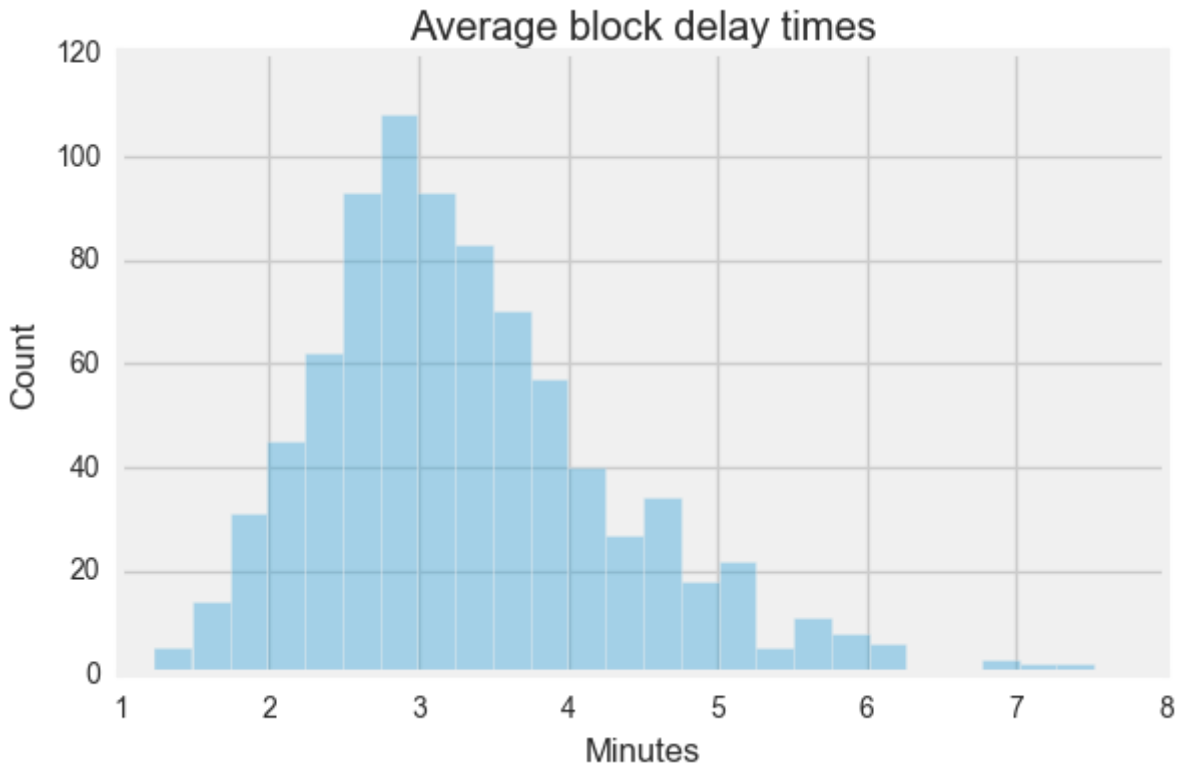
In [88]:
```
sns.distplot(df["average_gate_arrival_delay"], kde=False, label="Gate Arr
sns.distplot(df["average_airborne_delay"], kde=False, label="Airborne Del
sns.distplot(df["average_taxi_in_delay"], kde=False, label="Taxi In Delay
plt.legend(loc="best");
plt.title("Average arrival delay times");
plt.ylabel("Count");
plt.xlabel("Minutes");
```

Last executed 2016-11-06 22:23:15 in 985ms



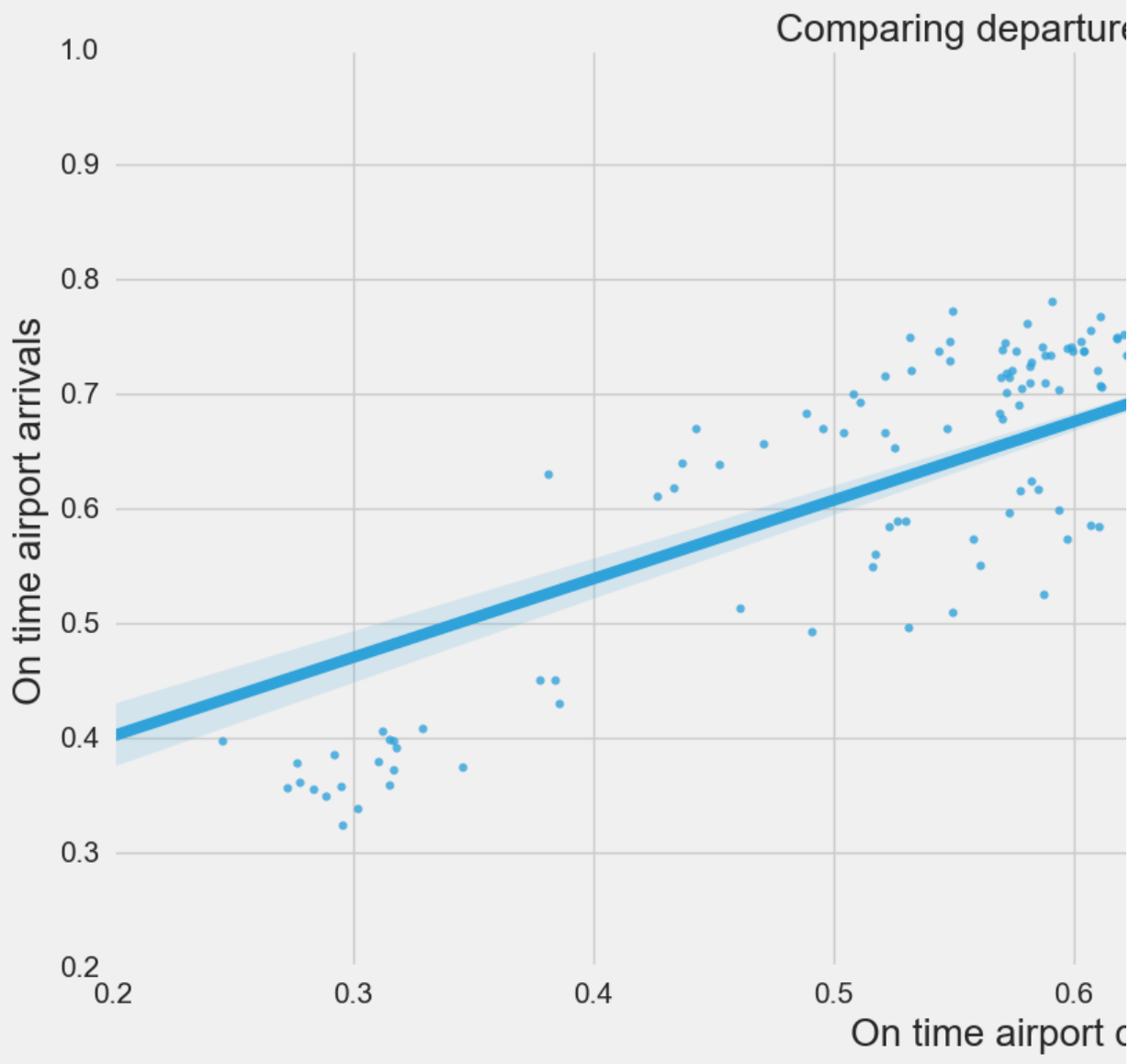
In [87]:
```
sns.distplot(df["average_block_delay"], kde=False);
plt.title("Average block delay times");
plt.ylabel("Count");
plt.xlabel("Minutes");
```

Last executed 2016-11-06 22:22:50 in 698ms



In [64]:
```
# percentage of on time arrivals
plt.subplots(figsize=(16,8));
sns.regplot(y="percent_on_time_gate_arrivals", x="percent_on_time_airport
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("On time airport arrivals", fontsize=20);
plt.xlabel("On time airport departures", fontsize=20);
plt.title("Comparing departures and arrivals");
```

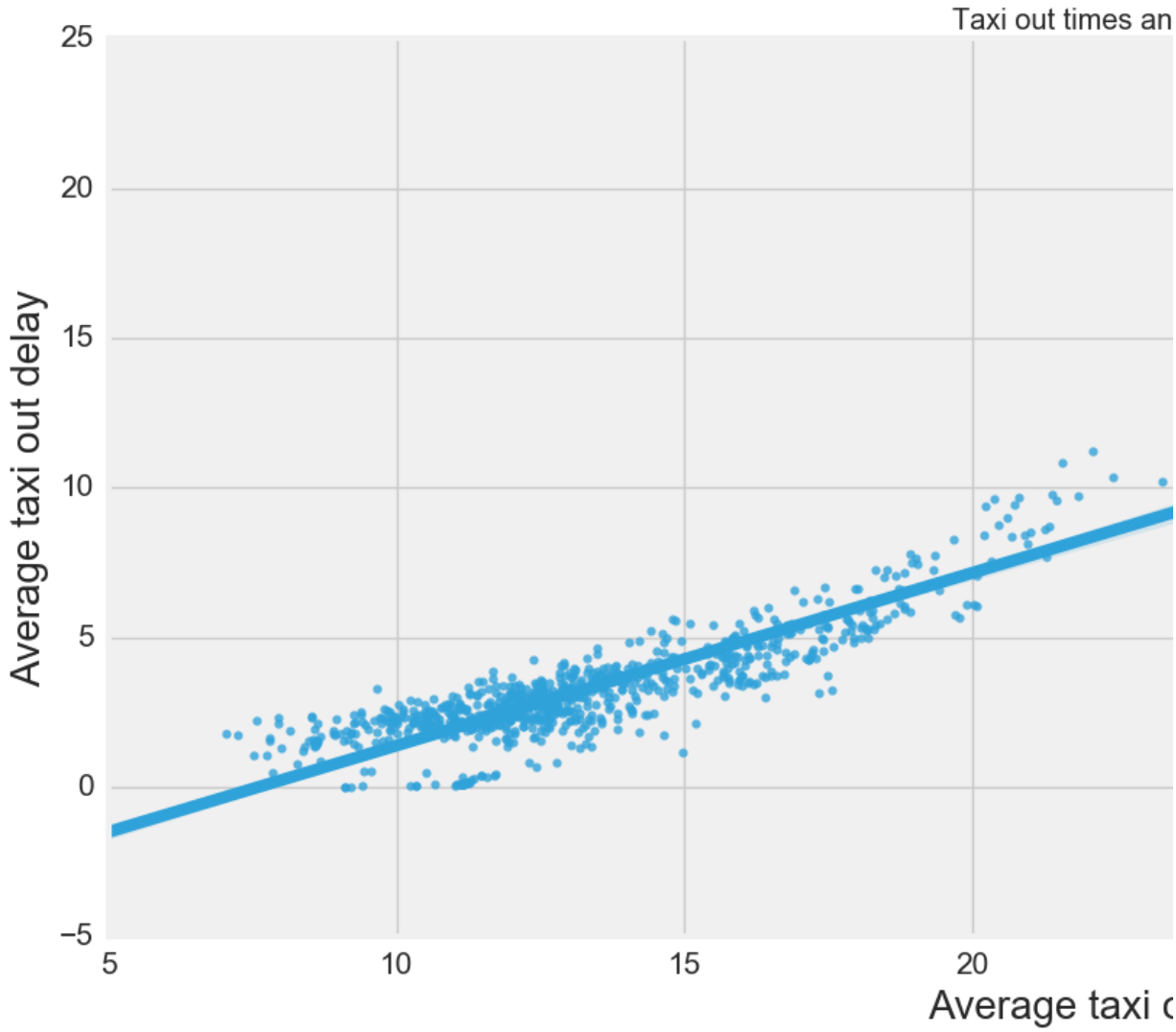
Last executed 2016-11-06 21:52:10 in 1.16s




```
# for year in df["year"].unique():
fig, ax = plt.subplots(figsize=(16,8));
sns.regplot(y="average_taxi_out_delay", x="average_taxi_out_time", data=d
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("Average taxi out delay", fontsize=20);
plt.xlabel("Average taxi out time", fontsize=20);
plt.title("Taxi out times and delays");
plt.show();
```

In [79]:
```
plt.subplots(figsize=(16,8));
sns.regplot(y="average_taxi_out_delay", x="average_taxi_out_time",data=df
plt.xticks(fontsize=15);
plt.yticks(fontsize=15);
plt.ylabel("Average taxi out delay", fontsize=20);
plt.xlabel("Average taxi out time", fontsize=20);
plt.title("Taxi out times and delays");
```

Last executed 2016-11-06 22:15:14 in 1.46s



In [78]:
```
le = preprocessing.LabelEncoder()
df["faa_num"] = le.fit_transform(df["faa_region"])
```

In [81]:
```
df["faa_num"].unique()
```

Last executed 2016-11-06 22:16:29 in 8ms

Out[81]:
```
array([7, 0, 6, 4, 2, 8, 3, 5, 1])
```

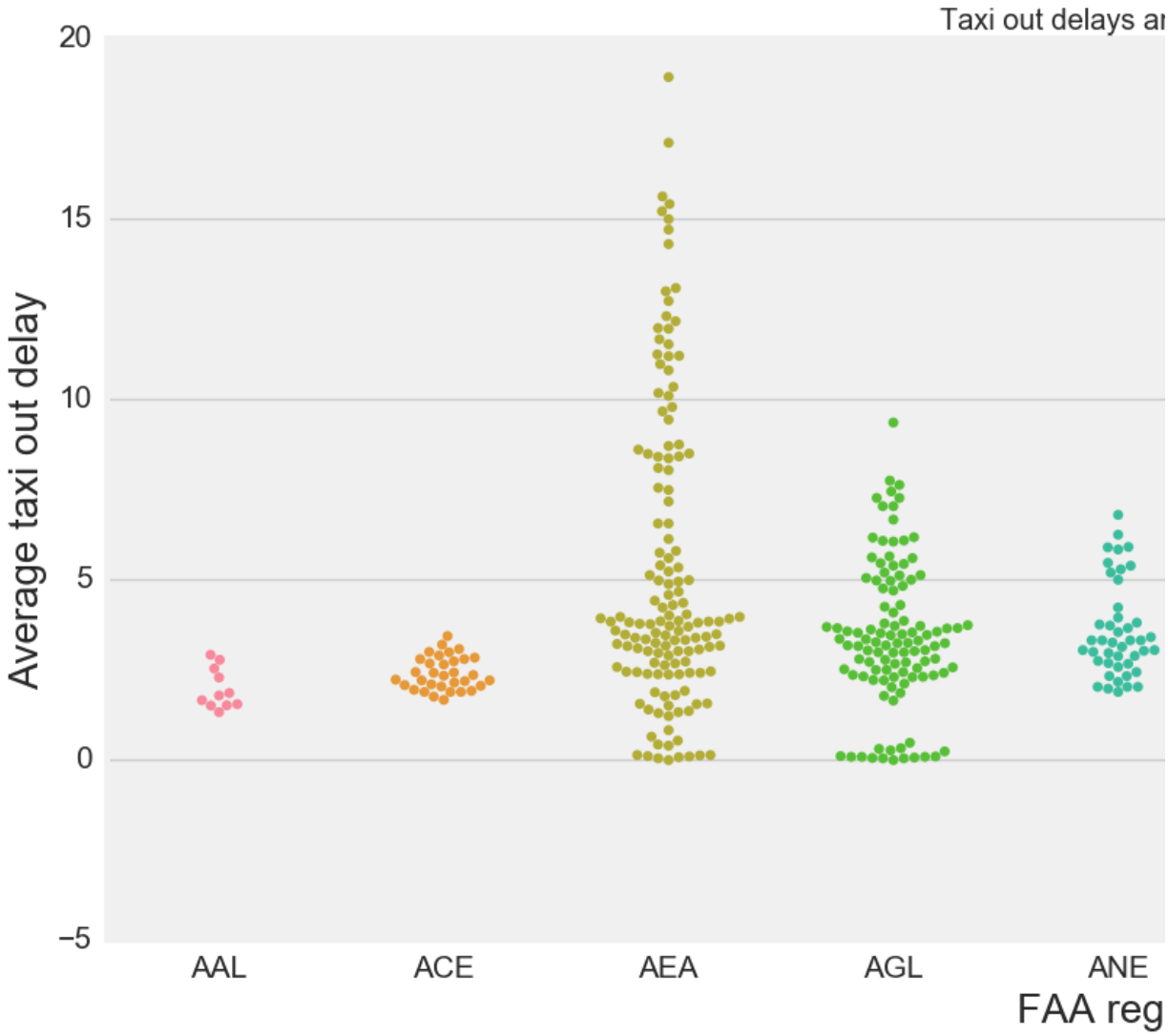
In [82]:
```
le.inverse_transform(df["faa_num"].unique())
```

Last executed 2016-11-06 22:16:46 in 8ms

Out[82]:
```
array(['ASW', 'AAL', 'ASO', 'ANE', 'AEA', 'AWP', 'AGL', 'ANM', 'ACE'], dt
```

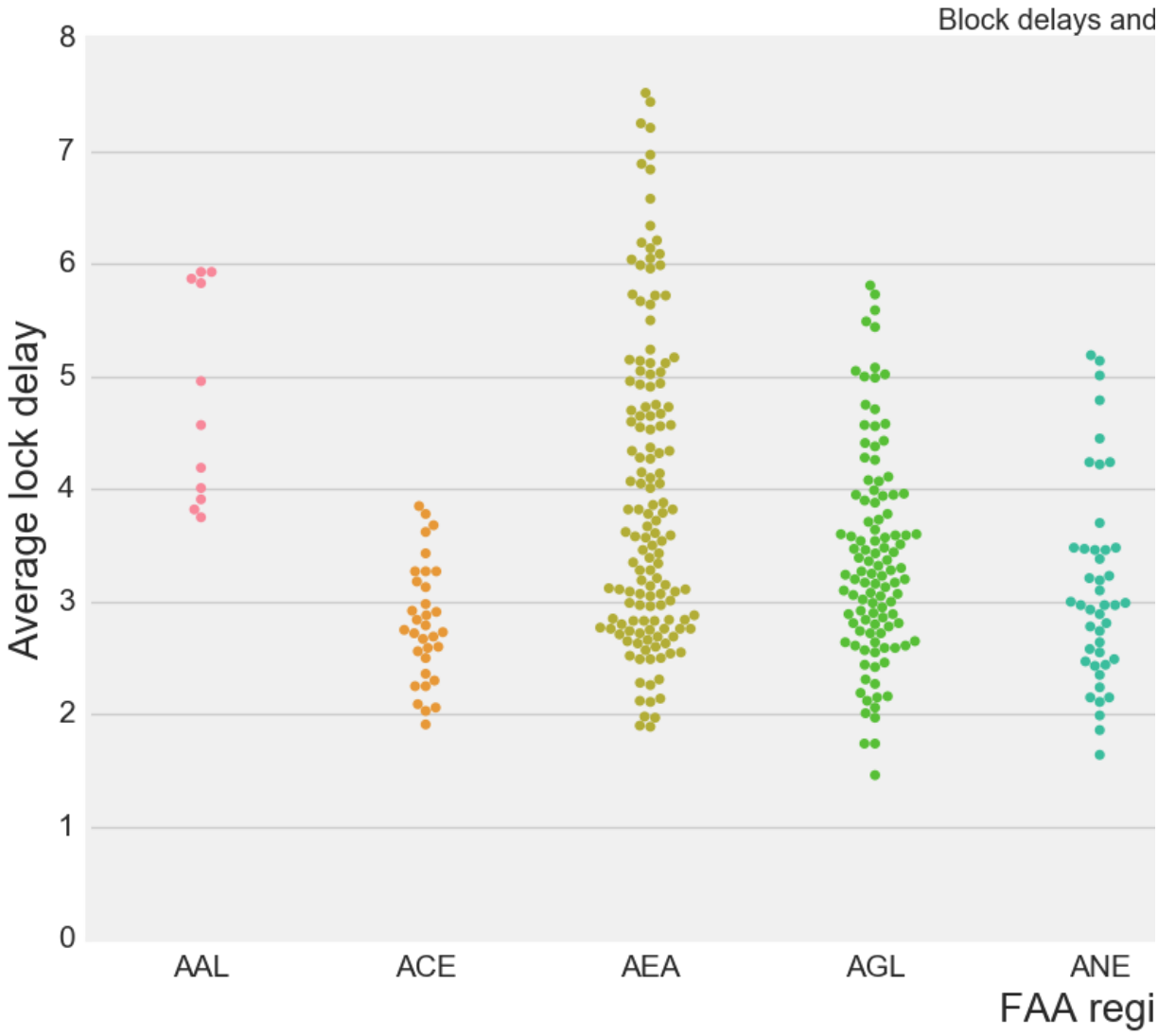
In [85]:
```
plt.subplots(figsize=(16,8));
sns.swarmplot(y="average_taxi_out_delay", x="faa_num",data=df);
plt.xticks(df["faa_num"].unique(), le.inverse_transform(df["faa_num"].uni
plt.yticks(fontsize=15);
plt.ylabel("Average taxi out delay", fontsize=20);
plt.xlabel("FAA region", fontsize=20);
plt.title("Taxi out delays and regions");
```

Last executed 2016-11-06 22:18:57 in 2.12s



In [86]:
```
plt.subplots(figsize=(16,8));
sns.swarmplot(y="average_block_delay", x="faa_num",data=df);
plt.xticks(df["faa_num"].unique(), le.inverse_transform(df["faa_num"].uni
plt.yticks(fontsize=15);
plt.ylabel("Average lock delay", fontsize=20);
plt.xlabel("FAA region", fontsize=20);
plt.title("Block delays and regions");
```

Last executed 2016-11-06 22:19:35 in 1.24s



1.0.3.2 Are there any unique values?

In [102]:
```
df.describe()
```

Last executed 2016-11-06 22:55:50 in 210ms

Out[102]:

	airport	locid	ap_name	alias	facility_type	faa_region	c

_arrivals	average_gate_departure_delay	average_taxi_out_time	average_taxi_out_delay	ave
	841.000000	841.000000	841.000000	84
	13.561403	13.703389	3.519750	16.
	4.746563	3.792181	2.391278	5.3
	5.350000	7.040000	0.000000	6.2
	10.910000	11.260000	2.210000	12.
	12.640000	12.810000	2.990000	15.
	14.950000	15.650000	4.080000	17.
	40.800000	35.760000	18.940000	40.

In [106]:
```
df.describe(include=["O"])
```

Last executed 2016-11-06 22:56:37 in 116ms

Out[106]:

	airport	locid	ap_name	alias	facility_type	faa_region	c
count	841	841	841	841	841	841	84
unique	77	77	77	77	1	9	65
top	LAS	LAS	THEODORE FRANCIS GREEN STATE	Honolulu Int'l Airport	Airport	AWP	L A
freq	11	11	11	11	841	192	44

facility_type and boundary_data_available have only one value each, so we can drop them

1.0.4 Part 3: Data Mining

1.0.4.1 3.1 Create Dummy Variables

In [121]:
```
faa = ["alaskan", "central", "eastern", "great_lakes", "new_england", "nc
       "southern", "southwest", "western_pacific"]
```

Last executed 2016-11-06 23:34:29 in 5ms

In [122]:
```
faa_ab = ['AAL', 'ACE', 'AEA', 'AGL', 'ANE', 'ANM', 'ASO', 'ASW', 'AWP']
```

Last executed 2016-11-06 23:34:30 in 5ms

In [133]:
```
faa_d = {i:j for i, j in zip(faa_ab, faa)}
```

Last executed 2016-11-06 23:36:23 in 6ms

In [134]:
```
faa_d
```

Last executed 2016-11-06 23:36:23 in 7ms

Out[134]:
```
{'AAL': 'alaskan',
 'ACE': 'central',
 'AEA': 'eastern',
 'AGL': 'great_lakes',
 'ANE': 'new_england',
 'ANM': 'northwest_mountain',
 'ASO': 'southern',
 'ASW': 'southwest',
 'AWP': 'western_pacific'}
```

In [140]:
```
df2 = df.copy()

df2["faa_region"] = df2["faa_region"].map(faa_d)

df2 = pd.get_dummies(df2, columns=["faa_region", "state", "ap_type"])
del df2["faa_num"]
del df2["facility_type"]
del df2["boundary_data_available"]
del df2["city"]
del df2["county"]
del df2["alias"]
del df2["ap_name"]
del df2["ap_type_Public Use"]
del df2["faa_region_alaskan"]
```

Last executed 2016-11-06 23:37:10 in 42ms

In [141]:
```
df2.columns
```

Last executed 2016-11-06 23:37:11 in 15ms

Out[141]:
```
Index([u'airport', u'year', u'departures_for_metric_computation',
       u'arrivals_for_metric_computation', u'percent_on_time_gate_departu
       u'percent_on_time_airport_departures', u'percent_on_time_gate_arri
       u'average_gate_departure_delay', u'average_taxi_out_time',
       u'average_taxi_out_delay', u'average_airport_departure_delay',
       u'average_airborne_delay', u'average_taxi_in_delay',
       u'average_block_delay', u'average_gate_arrival_delay', u'key', u'l
       u'latitude', u'longitude', u'faa_region_central', u'faa_region_eas
       u'faa_region_great_lakes', u'faa_region_new_england',
       u'faa_region_northwest_mountain', u'faa_region_southern',
       u'faa_region_southwest', u'faa_region_western_pacific', u'state_AK
       u'state_AL', u'state_AZ', u'state_CA', u'state_CO', u'state_CT',
       u'state_DC', u'state_FL', u'state_GA', u'state_HI', u'state_IL',
       u'state_IN', u'state_KY', u'state_LA', u'state_MA', u'state_MD',
       u'state_MI', u'state_MN', u'state_MO', u'state_NC', u'state_NE',
       u'state_NH', u'state_NJ', u'state_NM', u'state_NV', u'state_NY',
       u'state_OH', u'state_OR', u'state_PA', u'state_PR', u'state_RI',
       u'state_TN', u'state_TX', u'state_UT', u'state_WA', u'state_WI',
       u'ap_type_Federalized/Commercial'],
      dtype='object')
```

1.0.4.2 3.2 Format and Clean the Data

In [2]:
```
"s"
```

Last executed 2016-11-07 00:06:58 in 6ms

Out[2]:
```
's'
```

1.0.5 Part 4: Define the Data

1.0.5.1 4.1 Confirm that the dataset has a normal distribution. How can you tell?

In [ ]:

1.0.5.2 4.2 Find correlations in the data

In [ ]:

1.0.5.3 4.3 What is the value of understanding correlations before PCA?

Answer:

1.0.5.4 4.4 Validate your findings using statistical analysis

In [ ]:

1.0.5.5 4.5 How can you improve your overall analysis?

Answer:

1.0.6 Part 5: Perform a PCA

1.0.6.1 5.1 Conduct the PCA

In [ ]:

In [ ]:

1.0.7 Part 6: Additional Analysis

Include any other models you'd like to run here. These can include regressions, classifications, or

In [ ]:

In [ ]:

In [ ]:

1.0.8 Part 7: Write an analysis plan of your findings

Create a writeup on the interpretation of findings including an executive summary with conclusions

Type *Markdown* and LaTeX: α^2

Which operational features are most correlated with delays?

What should the airport's next steps be?

1.0.9 Bonus: Copy your Database to AWS

Make sure to properly document all of the features of your dataset

In [ ]:

1.0.10 Bonus: Create a 3-Dimensional Plot of your new dataset with PC

In [ ]: