Machine Learning

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1 India Rainfall Analysis

1.1 Motivation and Description

Monsoon prediction is clearly of great importance for India. Two types of rainfall predictions can be done, They are - Long term predictions: Predict rainfall over few weeks/months in advance. - Short term predic tions : Predict rainfall a few days in advance in specific locations.

Indian meteorological department provides forecasting data required for project. In this project we are planning to work on long term predictions of rainfall. The main motive of the project is to predict the amount of rainfall in a particular division or state well in advance. We predict the amount of rainfall using past data.

1.2 Dataset

- Dataset1 (dataset1) This dataset has average rainfall from 1951-2000 for each district, for every month.
- Dataset2 (dataset2) This dataset has average rainfall for every year from 1901-2015 for each state.

1.3 Methodology

- Converting data in to the correct format to conduct experiments.
- Make a good analysis of data and observe variation in the patterns of rainfall.
- Finally, we try to predict the average rainfall by separating data into training and testing. We apply various statistical and machine learning approaches(*SVM*, etc) in prediction and make analysis over various approaches. By using various approaches we try to minimize the error.

```
In [1]: import numpy as np # linear algebra
        import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv) import
        matplotlib.pyplot as plt import seaborn as sns
```

1.4 Types of graphs

- Bar graphs showing distribution of amount of rainfall.
- Distribution of amount of rainfall yearly, monthly, groups of months.
- Distribution of rainfall in subdivisions, districts form each month, groups of months.
- Heat maps showing correlation between amount of rainfall between months.

```
In [2]: data = pd.read_csv("../data/rainfall_in_india_1901-2015.csv",sep=",")
        data = data.fillna(data.mean()) data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4116 entries, 0 to 4115
```

```
Data columns (total 19 columns):
SUBDIVISION     4116 non-null object
YEAR            4116 non-null int64
JAN             4116 non-null float64
FEB             4116 non-null float64
MAR             4116 non-null float64
APR             4116 non-null float64
MAY             4116 non-null float64
JUN             4116 non-null float64
JUL             4116 non-null float64
AUG             4116 non-null float64
SEP             4116 non-null float64
OCT             4116 non-null float64
NOV             4116 non-null float64
DEC             4116 non-null float64
ANNUAL          4116 non-null float64
Jan-Feb         4116 non-null float64
Mar-May         4116 non-null float64
Jun-Sep         4116 non-null float64
Oct-Dec         4116 non-null float64
dtypes: float64(17), int64(1), object(1)
memory usage: 611.0+ KB
```

1.5 Dataset-1 Description

- Data has 36 sub divisions and 19 attributes (individual months, annual, combinations of 3 consecutive months).
- For some of the subdivisions data is from 1950 to 2015.
- All the attributes has the sum of amount of rainfall in mm.

In [3]: data.head()

Out[3]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN \
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7

	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL	Jan-Feb	Mar-May \
0	365.1	481.1	332.6	388.5	558.2	33.6	3373.2	136.3	560.3
1	228.9	753.7	666.2	197.2	359.0	160.5	3520.7	159.8	458.3
2	728.4	326.7	339.0	181.2	284.4	225.0	2957.4	156.7	236.1
3	502.0	160.1	820.4	222.2	308.7	40.1	3079.6	24.1	506.9
4	368.7	330.5	297.0	260.7	25.4	344.7	2566.7	1.3	309.7

	Jun-Sep	Oct-Dec
0	1696.3	980.3

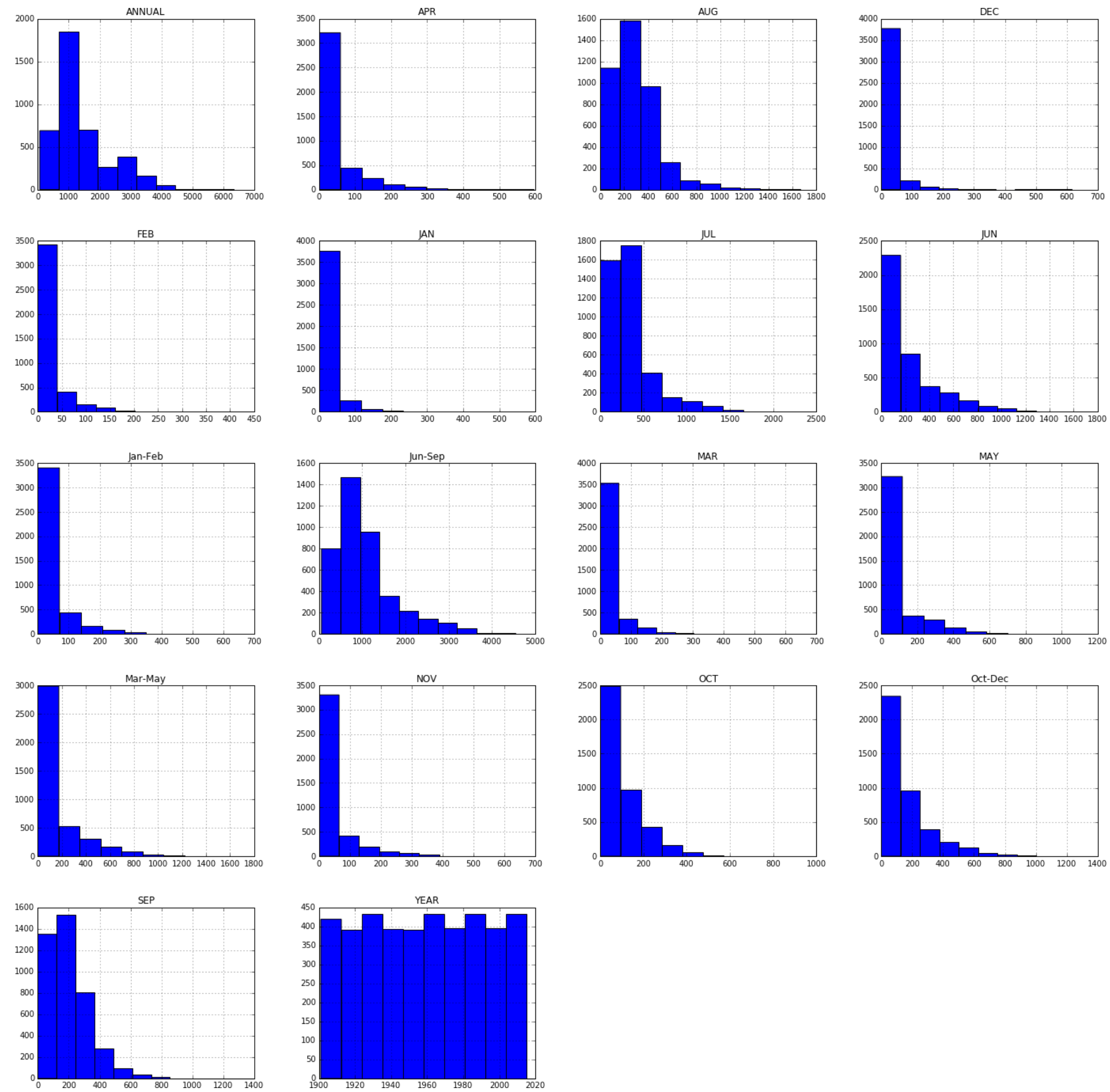
```
1    2185.9 716.7
2    1874.0 690.6
3    1977.6 571.0
4    1624.9 630.8
```

In [4]: data.describe()

Out[4]:

```
                  YEAR          JAN          FEB          MAR          APR \
count   4116.000000 4116.000000 4116.000000 4116.000000 4116.000000
Mean    1958.218659 18.957320 21.805325 27.359197 43.127432
Std       33.140898 33.569044 35.896396 46.925176 67.798192
Min     1901.000000    0.000000    0.000000    0.000000    0.000000
25%     1930.000000    0.600000    0.600000    1.000000    3.000000
50%     1958.000000    6.000000    6.700000     7.900000 15.700000
75%     1987.000000 22.125000 26.800000 31.225000 49.825000
Max     2015.000000 583.700000 403.500000 605.600000 595.100000

                   MAY          JUN          JUL          AUG          SEP \
count   4116.000000 4116.000000 4116.000000 4116.000000 4116.000000
Mean      85.745417 230.234444 347.214334 290.263497 197.361922
Std      123.189974 234.568120 269.310313 188.678707 135.309591
Min         0.000000    0.400000    0.000000    0.000000    0.100000
25%              8.600000 70.475000 175.900000 156.150000 100.600000
50%       36.700000 138.900000 284.900000 259.500000 174.100000
75%       96.825000 304.950000 418.225000 377.725000 265.725000
Max     1168.600000 1609.900000 2362.800000 1664.600000 1222.000000

                   OCT          NOV          DEC       ANNUAL        Jan-Feb \
count 4116.000000 4116.000000 4116.000000 4116.000000 4116.000000
Mean 95.507009 39.866163 18.870580 1411.008900 40.747786  Std 99.434452
68.593545 42.318098 900.986632 59.265023  min 0.000000 0.000000 0.000000
62.300000 0.000000 25% 14.600000 0.700000 0.100000 806.450000 4.100000
50% 65.750000 9.700000 3.100000 1125.450000 19.300000  75% 148.300000
45.825000 17.700000 1635.100000 50.300000  max 948.300000 648.900000
617.500000 6331.100000 699.500000


            Mar-May  Jun-Sep       Oct-Dec count
4116.000000 4116.000000 4116.000000
mean 155.901753 1064.724769 154.100487           std
     201.096692 706.881054 166.678751            min
     0.000000 57.400000     0.000000             25%
     24.200000 574.375000 34.200000
50%   75.200000   882.250000   98.800000      75%
196.900000    1287.550000    212.600000       max
1745.800000 4536.900000 1252.500000
```

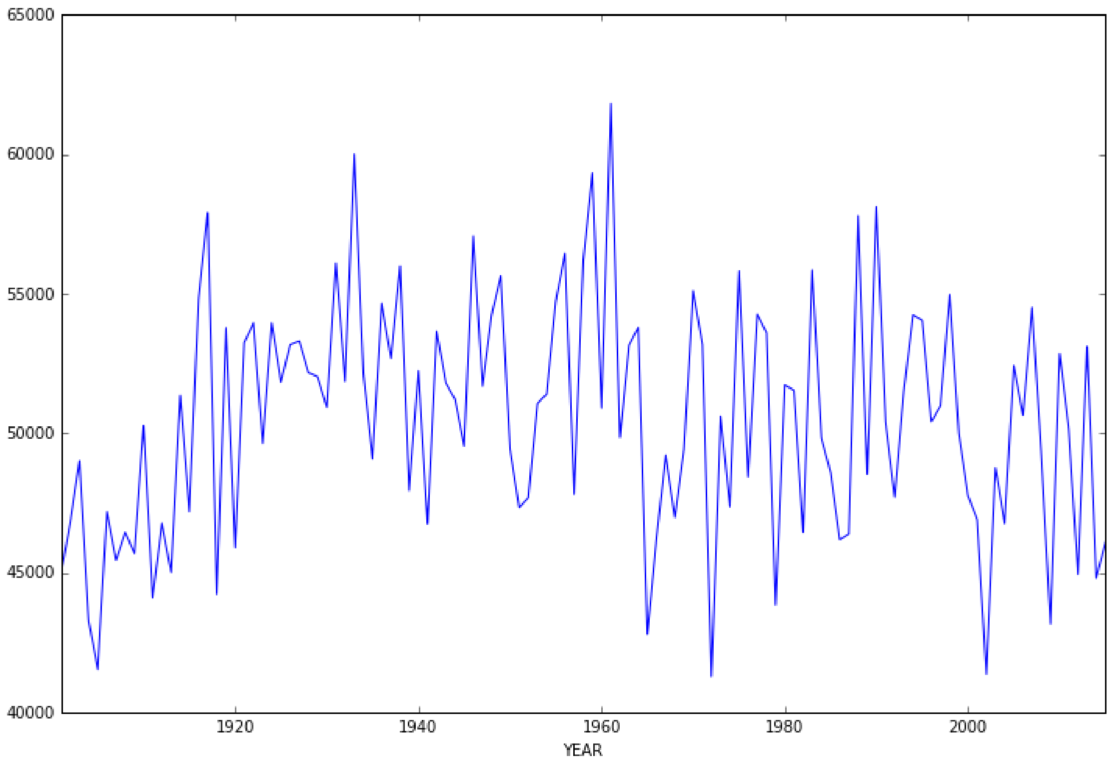
In [5]: data.hist(figsize=(24,24));



1.6 Observations

- Above histograms show the distribution of rainfall over months.
- Observed increase in amount of rainfall over months July, August, September.

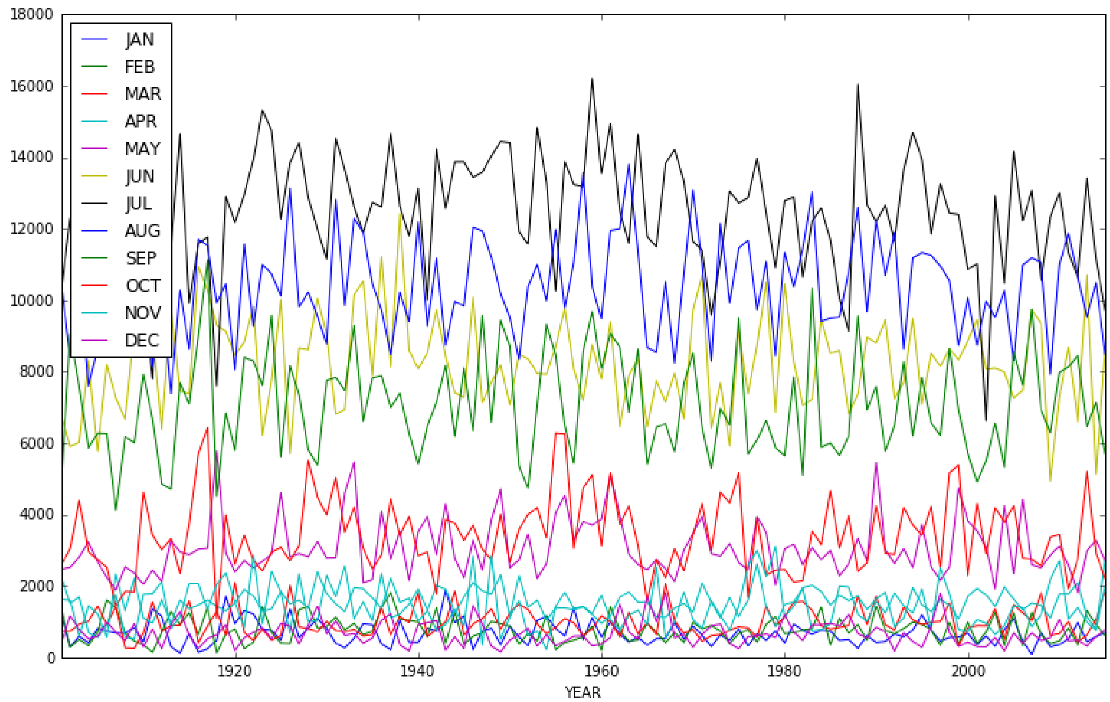
In [6]:
```
data.groupby("YEAR").sum()['ANNUAL'].plot(figsize=(12,8));
```



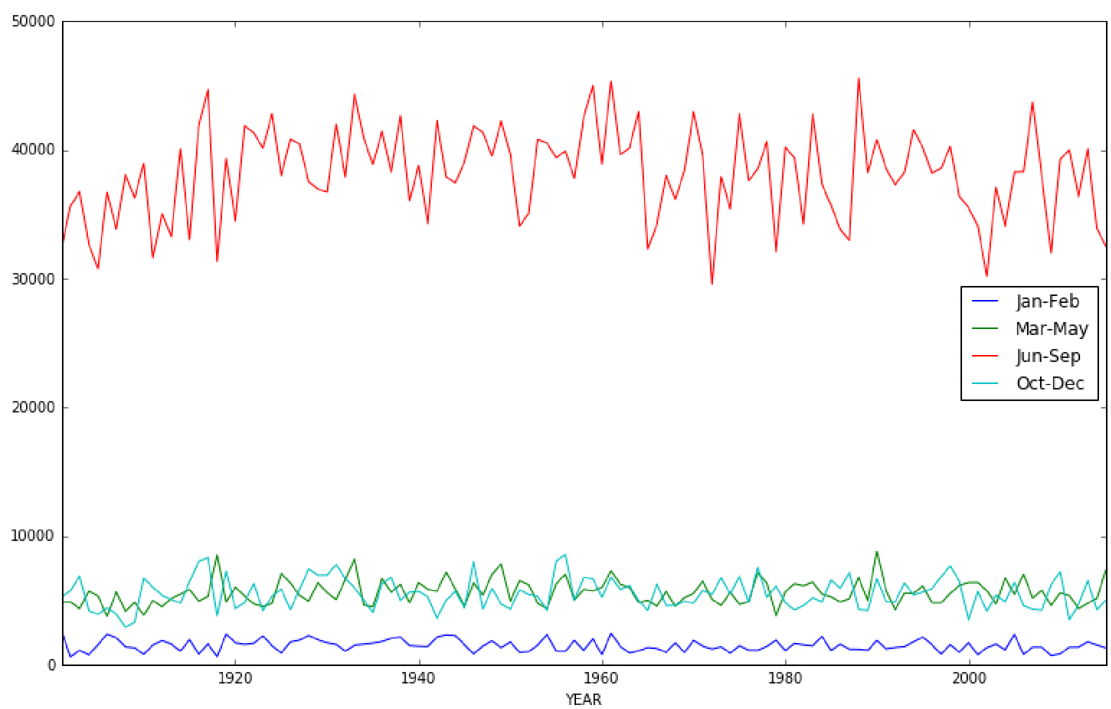
1.7 Observations

- Shows distribution of rainfall over years.
- Observed high amount of rainfall in 1950s.

```
In [7]: data[['YEAR', 'JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                              'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].groupby("YEAR").sum().plot(figsize=(13,8));
```




```
In [8]: data[['YEAR','Jan-Feb', 'Mar-May',
             'Jun-Sep', 'Oct-Dec']].groupby("YEAR").sum().plot(figsize=(13,8));
```

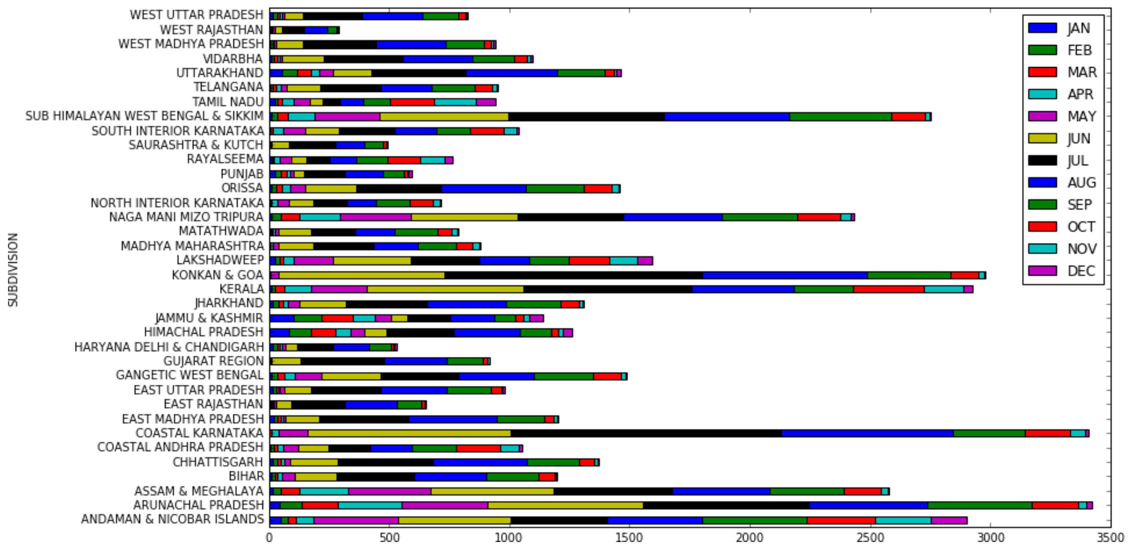


1.8 Observations

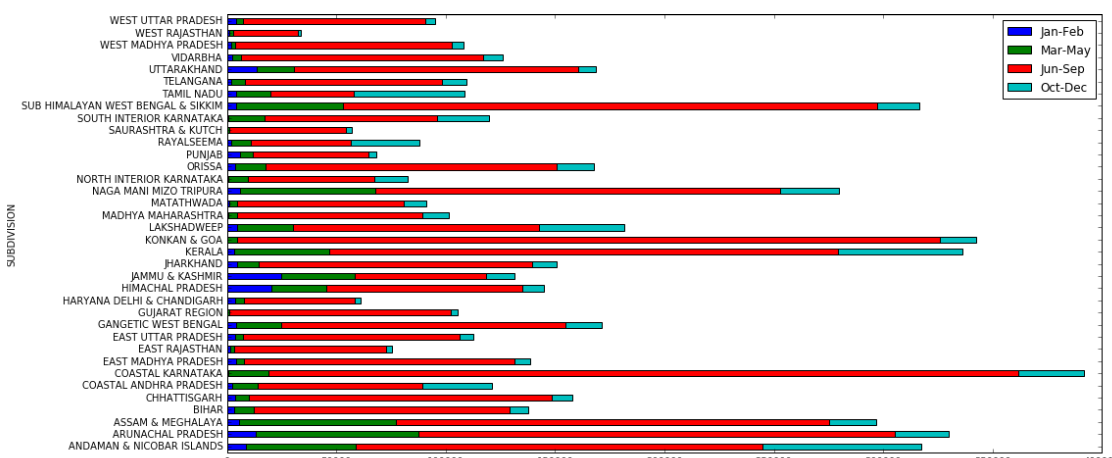
- The above two graphs show the distribution of rainfall over months.

- The graphs clearly shows that amount of rainfall in high in the months july, aug, sep which is monsoon season in India.

In [9]:
```
data[['SUBDIVISION', 'JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                    'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].groupby("SUBDIVISION").mean().plot.barh(stacked=True
```



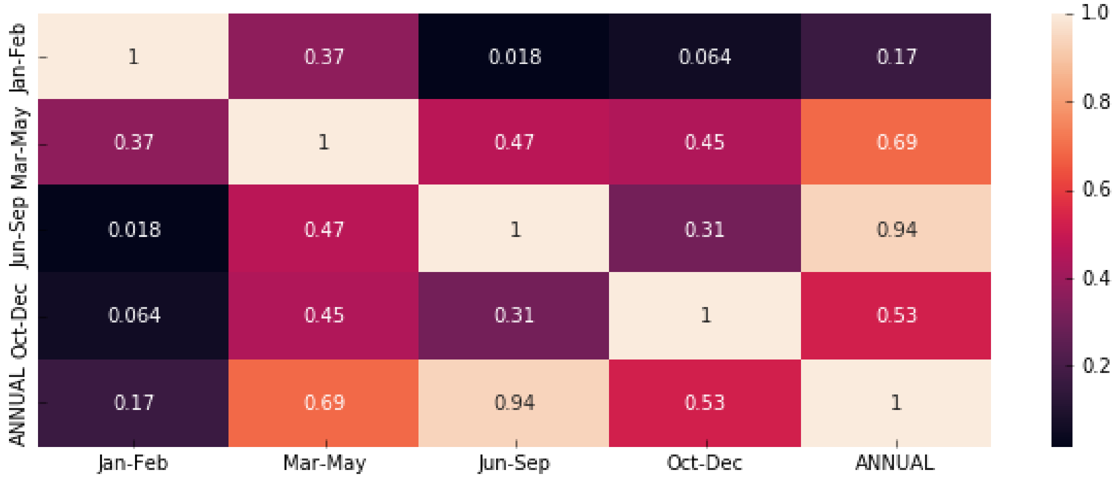
In [10]:
```
data[['SUBDIVISION', 'Jan-Feb', 'Mar-May',
                    'Jun-Sep', 'Oct-Dec']].groupby("SUBDIVISION").sum().plot.barh(stacked=True,figsize=(16,
```



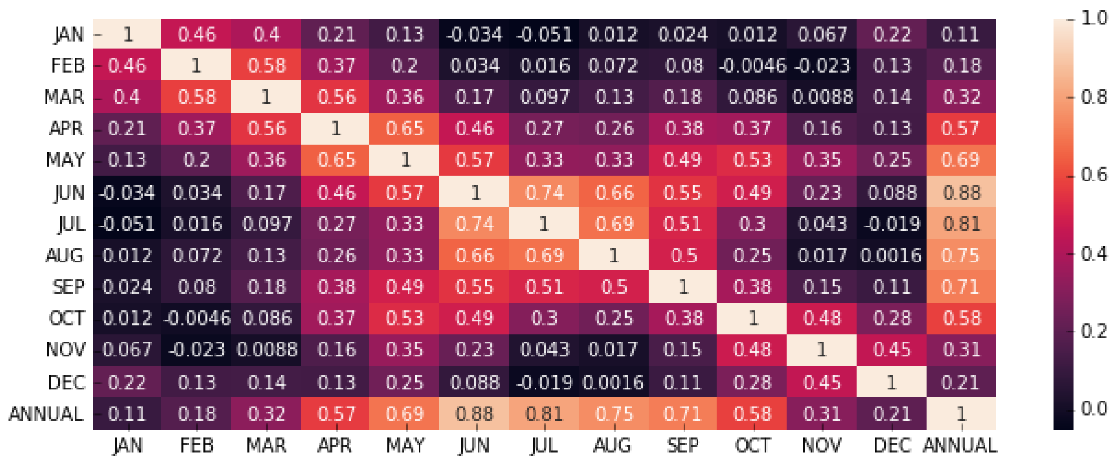
1.9 Observations

- Above two graphs shows that the amount of rainfall is reasonably good in the months of march, april, may in eastern India.

In [11]:
```
plt.figure(figsize=(11,4)) sns.heatmap(data[['Jan-Feb','Mar-May','Jun-Sep','Oct-
        Dec','ANNUAL']].corr(),annot=True) plt.show()
```




```
In [12]: plt.figure(figsize=(11,4))
         sns.heatmap(data[['JAN','FEB','MAR','APR','MAY','JUN','JUL','AUG','SEP','OCT','NOV','DEC','ANN plt.show()
```



1.10 Observations

- **Heat Map** shows the co-relation(dependency) between the amounts of rainfall over months.
- From above it is clear that if amount of rainfall is high in the months of july, august, september then the amount of rainfall will be high annually.
- It is also obwserved that if amount of rainfall in good in the months of october, november, december then the rainfall is going to b good in the overall year.

```
In [13]: #Function to plot the graphs def
         plot_graphs(groundtruth, prediction, title):
             N = 9 ind = np.arange(N) # the x locations for the groups
             width = 0.27 # the width of the bars
```

```
    fig = plt.figure()
    fig.suptitle(title, fontsize=12) ax =
    fig.add_subplot(111) rects1 = ax.bar(ind, groundtruth,
    width, color='r') rects2 = ax.bar(ind+width, prediction,
    width, color='g')

    ax.set_ylabel("Amount of rainfall") ax.set_xticks(ind+width) ax.set_xticklabels( ('APR',
    'MAY', 'JUN', 'JUL','AUG', 'SEP', 'OCT', 'NOV', 'DEC') ) ax.legend( (rects1[0], rects2[0]), ('Ground
    truth', 'Prediction') )

#       autolabel(rects1)
    for rect in rects1:
        h = rect.get_height()
        ax.text(rect.get_x()+rect.get_width()/2., 1.05*h, '%d'%int(h), ha='center',
                va='bottom')
    for rect in rects2:
        h = rect.get_height()
        ax.text(rect.get_x()+rect.get_width()/2., 1.05*h, '%d'%int(h),
                ha='center', va='bottom')
#       autolabel(rects2)

    plt.show()
```

1.11 Predictions

- For prediction we formatted data in the way, given the rainfall in the last three months we try to predict the rainfall in the next consecutive month.
- For all the experiments we used 80:20 training and test ratio.
    - Linear regression
    - SVR
    - Artificial neural nets
- Tersting metrics: We used Mean absolute error to train the models.
- We also shown the amount of rainfall actually and predicted with the histogram plots.
- We did two types of trainings once training on complete dataset and other with training with only telangana data
- All means are standard deviation observations are written, first one represents ground truth, second one represents predictions.

```
In [14]: # seperation of training and testing data from
         sklearn.model_selection import train_test_split from
         sklearn.metrics import mean_absolute_error
         division_data = np.asarray(data[['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG', 'SEP', 'OCT',
                'NOV', 'DEC']])

         X = None; y = None for i in
         range(division_data.shape[1]-3):
             if X is None:
```

```
                X = division_data[:, i:i+3] y
                = division_data[:, i+3]
            else:
                X = np.concatenate((X, division_data[:, i:i+3]), axis=0) y =
                np.concatenate((y, division_data[:, i+3]), axis=0)

        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_state=42)
```

```
In [15]: #test 2010 temp = data[['SUBDIVISION','JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG',
         'SEP', 'OCT', 'NOV', 'DEC']].loc[data['YEAR'] == 2010]
data_2010 = np.asarray(temp[['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].loc[temp['SUBDIVISION'] == 'TELANGANA'])

        X_year_2010 = None; y_year_2010 = None for i
        in range(data_2010.shape[1]-3):
            if X_year_2010 is None:
                X_year_2010 = data_2010[:, i:i+3] y_year_2010 =
                data_2010[:, i+3]
            else:
                X_year_2010 = np.concatenate((X_year_2010, data_2010[:, i:i+3]), axis=0) y_year_2010 =
                np.concatenate((y_year_2010, data_2010[:, i+3]), axis=0)
```

```
In [16]: #test 2005 temp = data[['SUBDIVISION','JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG',
         'SEP', 'OCT', 'NOV', 'DEC']].loc[data['YEAR'] == 2005]
data_2005 = np.asarray(temp[['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].loc[temp['SUBDIVISION'] == 'TELANGANA'])

        X_year_2005 = None; y_year_2005 = None for i
        in range(data_2005.shape[1]-3):
            if X_year_2005 is None:
                X_year_2005 = data_2005[:, i:i+3] y_year_2005 =
                data_2005[:, i+3]
            else:
                X_year_2005 = np.concatenate((X_year_2005, data_2005[:, i:i+3]), axis=0) y_year_2005 =
                np.concatenate((y_year_2005, data_2005[:, i+3]), axis=0)
```

```
In [17]: #terst 2015 temp = data[['SUBDIVISION','JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG',
         'SEP', 'OCT', 'NOV', 'DEC']].loc[data['YEAR'] == 2015]
data_2015 = np.asarray(temp[['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].loc[temp['SUBDIVISION'] == 'TELANGANA'])

        X_year_2015 = None; y_year_2015 = None for
        i in range(data_2015.shape[1]-3): if
        X_year_2015 is None:
                X_year_2015 = data_2015[:, i:i+3] y_year_2015 =
                data_2015[:, i+3]
            else:
                X_year_2015 = np.concatenate((X_year_2015, data_2015[:, i:i+3]), axis=0) y_year_2015 =
                np.concatenate((y_year_2015, data_2015[:, i+3]), axis=0)
```

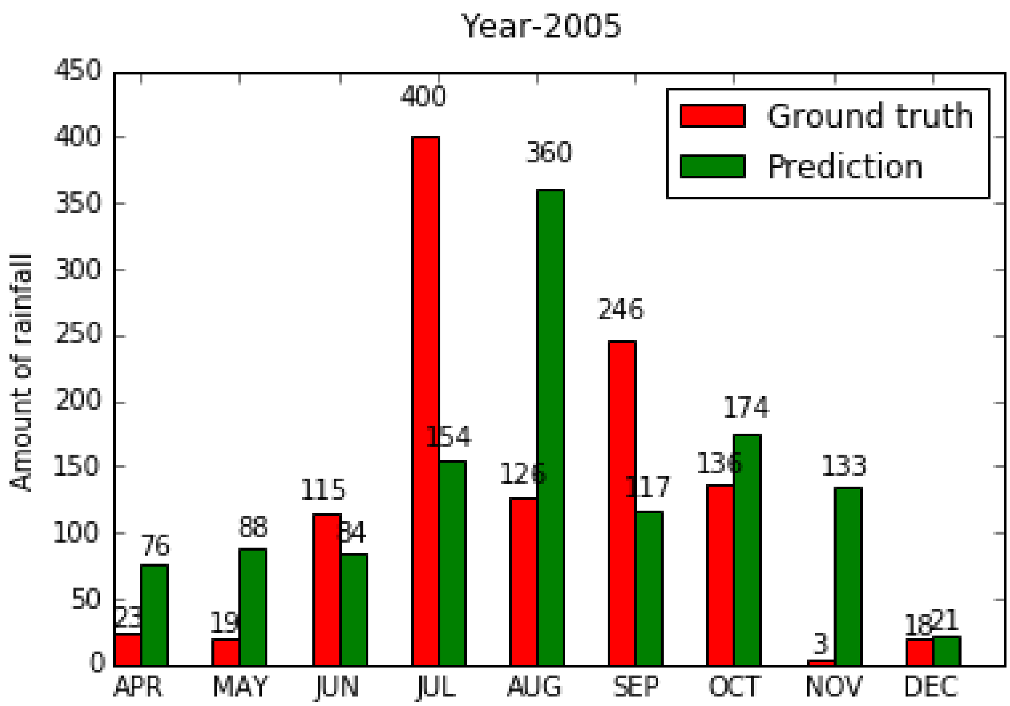
In [18]:
```
from sklearn import linear_model

# linear model reg =
linear_model.ElasticNet(alpha=0.5)
reg.fit(X_train, y_train) y_pred =
reg.predict(X_test) print
mean_absolute_error(y_test, y_pred)
```

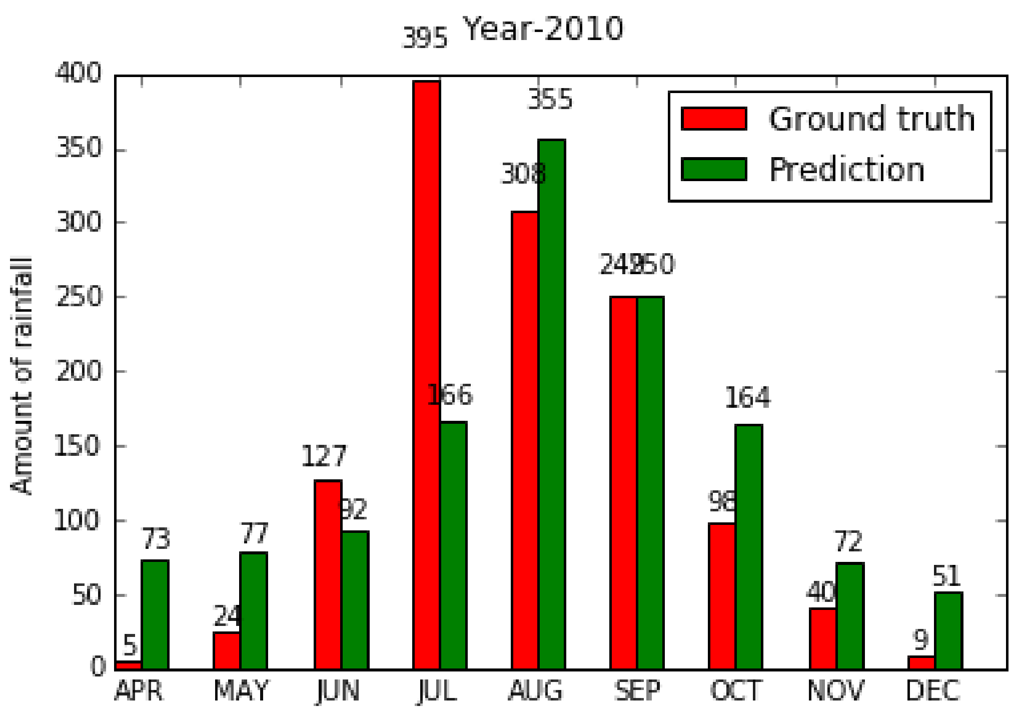
96.32435229744095

In [19]:
```
#2005 y_year_pred_2005 =
reg.predict(X_year_2005)
#2010
y_year_pred_2010 = reg.predict(X_year_2010) y_year_pred_2015 =

reg.predict(X_year_2015)

print "MEAN 2005"
print np.mean(y_year_2005),np.mean(y_year_pred_2005) print
"Standard deviation 2005"
print np.sqrt(np.var(y_year_2005)),np.sqrt(np.var(y_year_pred_2005))


print "MEAN 2010"
print np.mean(y_year_2010),np.mean(y_year_pred_2010) print
"Standard deviation 2010"
print np.sqrt(np.var(y_year_2010)),np.sqrt(np.var(y_year_pred_2010))


print "MEAN 2015"
print np.mean(y_year_2015),np.mean(y_year_pred_2015) print
"Standard deviation 2015"
print np.sqrt(np.var(y_year_2015)),np.sqrt(np.var(y_year_pred_2015))


plot_graphs(y_year_2005,y_year_pred_2005,"Year-2005")
plot_graphs(y_year_2010,y_year_pred_2010,"Year-2010")
plot_graphs(y_year_2015,y_year_pred_2015,"Year-2015")
```

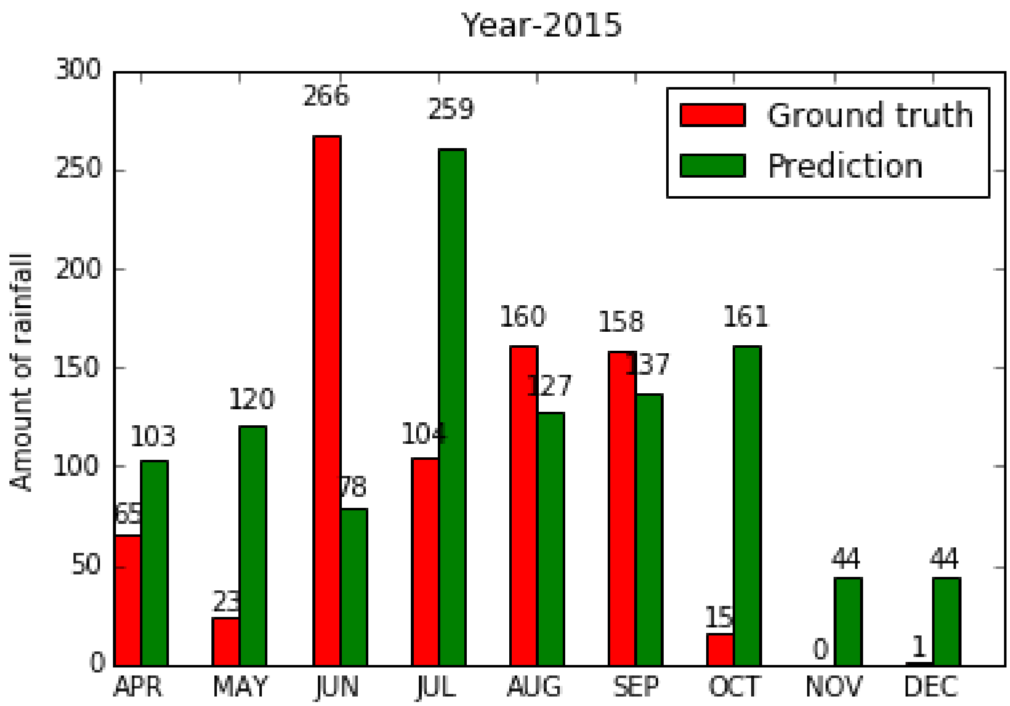
MEAN 2005
121.2111111111111 134.68699821349824
Standard deviation 2005
123.77066107608005 90.86310230416397 MEAN
2010
139.93333333333334 144.8050132651592
Standard deviation 2010
135.71320250194282 95.94931363601675 MEAN
2015
88.52222222222223 119.64752006738864
Standard deviation 2015

86.62446123324875 62.36355370163346





2



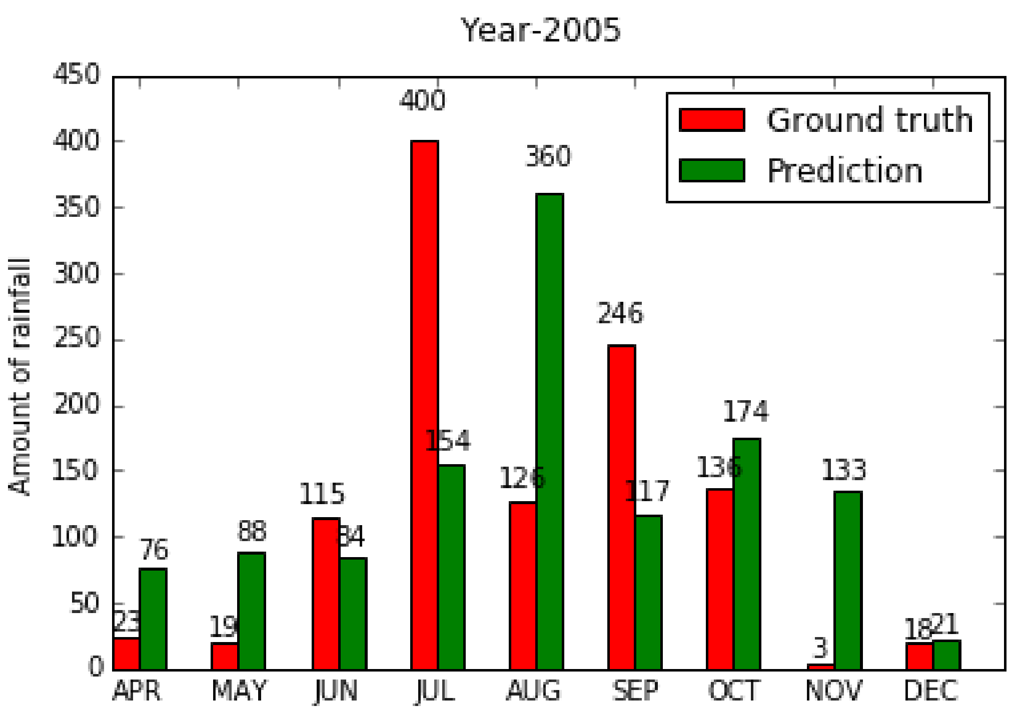

```
In [20]: from sklearn.svm import SVR
         # SVM model clf  =  SVR(gamma='auto',   C=0.1,
         epsilon=0.2) clf.fit(X_train, y_train) y_pred
         =           clf.predict(X_test)           print
         mean_absolute_error(y_test, y_pred)
```

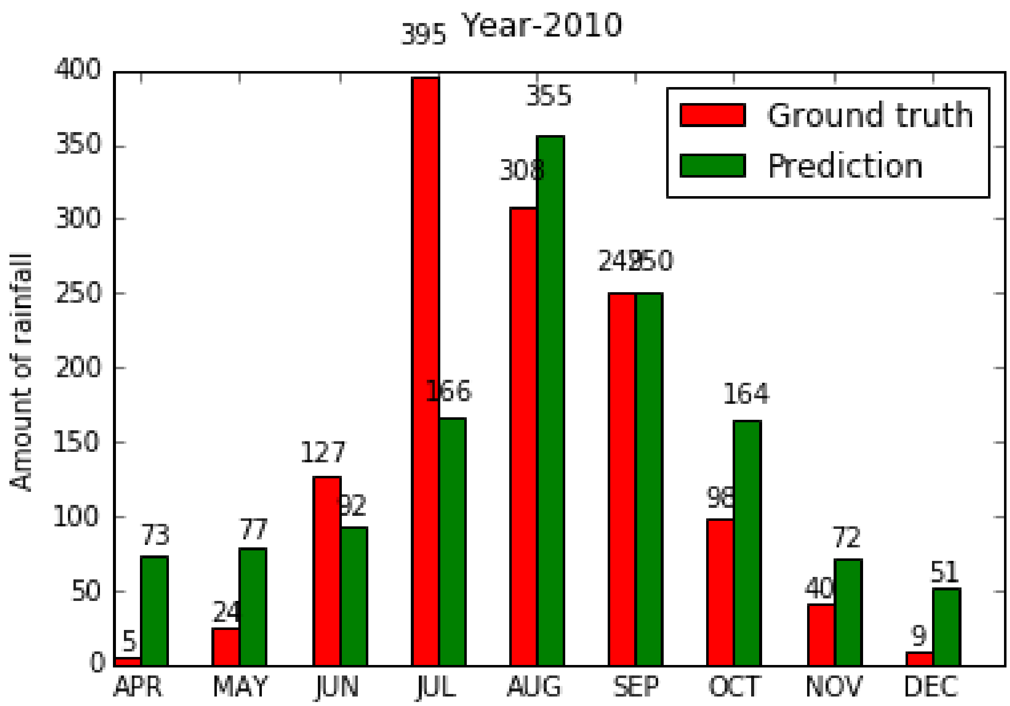
127.1600615632603

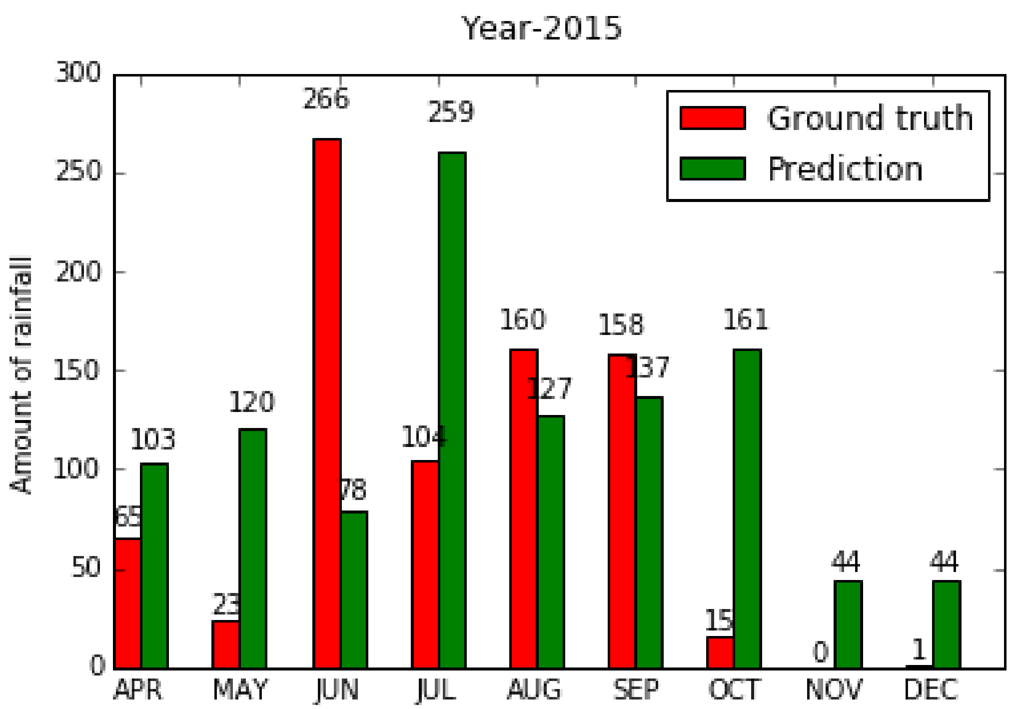
```
In       [21]:       #2005      y_year_pred_2005        =
         reg.predict(X_year_2005)

         #2010
         y_year_pred_2010 = reg.predict(X_year_2010)

         #2015            y_year_pred_2015              =
         reg.predict(X_year_2015) print "MEAN 2005"
         print  np.mean(y_year_2005),np.mean(y_year_pred_2005)   print
         "Standard deviation 2005"
         print np.sqrt(np.var(y_year_2005)),np.sqrt(np.var(y_year_pred_2005))

         print "MEAN 2010"
         print  np.mean(y_year_2010),np.mean(y_year_pred_2010)   print
         "Standard deviation 2010"
         print np.sqrt(np.var(y_year_2010)),np.sqrt(np.var(y_year_pred_2010))
```

```
        print "MEAN 2015"
        print  np.mean(y_year_2015),np.mean(y_year_pred_2015)   print
        "Standard deviation 2015"
        print np.sqrt(np.var(y_year_2015)),np.sqrt(np.var(y_year_pred_2015))
plot_graphs(y_year_2005,y_year_pred_2005,"Year-2005")
        plot_graphs(y_year_2010,y_year_pred_2010,"Year-2010")
        plot_graphs(y_year_2015,y_year_pred_2015,"Year-2015")
```

```
MEAN 2005
121.2111111111111 134.68699821349824
Standard deviation 2005
123.77066107608005 90.86310230416397
MEAN 2010
139.93333333333334  144.8050132651592  Standard
deviation 2010
135.71320250194282  95.94931363601675  MEAN
2015
88.52222222222223 119.64752006738864
Standard deviation 2015
86.62446123324875 62.36355370163346
```







In [22]:
```
from keras.models import Model from keras.layers import
Dense, Input, Conv1D, Flatten

# NN model
```

```
inputs = Input(shape=(3,1)) x = Conv1D(64, 2, padding='same',
activation='elu')(inputs) x = Conv1D(128, 2, padding='same',
activation='elu')(x) x = Flatten()(x) x = Dense(128,
activation='elu')(x) x = Dense(64, activation='elu')(x) x =
Dense(32, activation='elu')(x) x = Dense(1,
activation='linear')(x) model = Model(inputs=[inputs],
outputs=[x])
model.compile(loss='mean_squared_error', optimizer='adamax', metrics=['mae']) model.summary()
```

```
/home/sudheer.achary/.local/lib/python2.7/site-packages/h5py/_init_.py:36: FutureWarning: Conversion from
._conv import register_converters as _register_converters Using TensorFlow backend.
```

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 3, 1)	0
conv1d_1 (Conv1D)	(None, 3, 64)	192
conv1d_2 (Conv1D)	(None, 3, 128)	16512
flatten_1 (Flatten)	(None, 384)	0
dense_1 (Dense)	(None, 128)	49280
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 1)	33

```
Total params: 76,353
Trainable params: 76,353
Non-trainable params: 0
```

In [23]:
```
model.fit(x=np.expand_dims(X_train, axis=2), y=y_train, batch_size=64, epochs=10, verbose=1, v
y_pred = model.predict(np.expand_dims(X_test, axis=2)) print mean_absolute_error(y_test, y_pred)
```

```
Train on 30005 samples, validate on 3334 samples
Epoch 1/10
30005/30005 [==============================] - 3s 111us/step - loss: 19589.7591 - mean_absolute_error:
Epoch 2/10
30005/30005 [==============================] - 2s 53us/step - loss: 18582.2211 - mean_absolute_error:
Epoch 3/10
30005/30005 [==============================] - 2s 54us/step - loss: 18466.6604 - mean_absolute_error:
Epoch 4/10
30005/30005 [==============================] - 2s 54us/step - loss: 18482.5326 - mean_absolute_error:
```

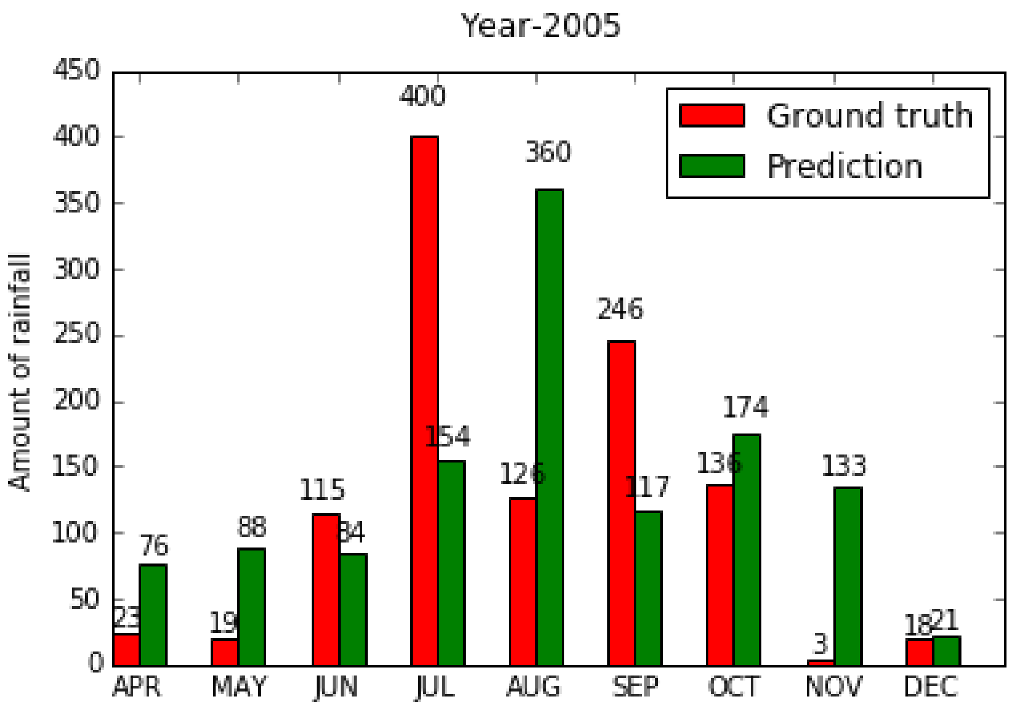
```
Epoch 5/10
30005/30005 [==============================] - 2s 54us/step - loss: 18358.7726 - mean_absolute_error:
Epoch 6/10
30005/30005 [==============================] - 2s 53us/step - loss: 18312.5666 - mean_absolute_error:
Epoch 7/10
30005/30005 [==============================] - 2s 54us/step - loss: 18236.9615 - mean_absolute_error:
Epoch 8/10
30005/30005 [==============================] - 2s 54us/step - loss: 18118.3601 - mean_absolute_error:
Epoch 9/10
30005/30005 [==============================] - 2s 54us/step - loss: 18193.9362 - mean_absolute_error:
Epoch 10/10
30005/30005 [==============================] - 2s 54us/step - loss: 18007.9055 - mean_absolute_error:
92.28250624049363
```

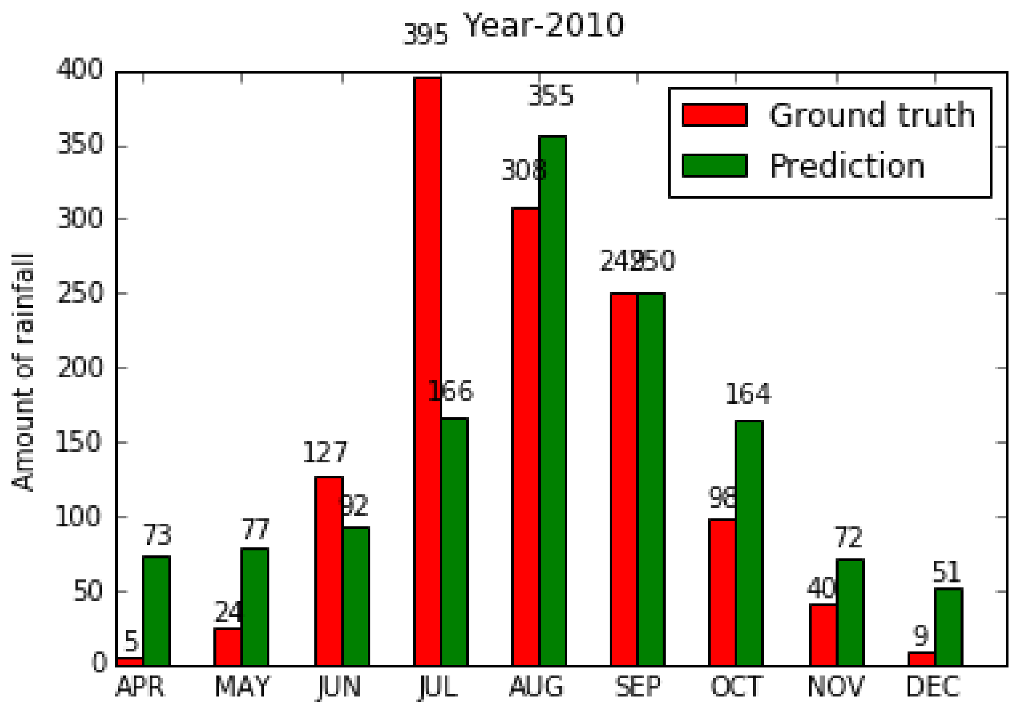
In [24]:

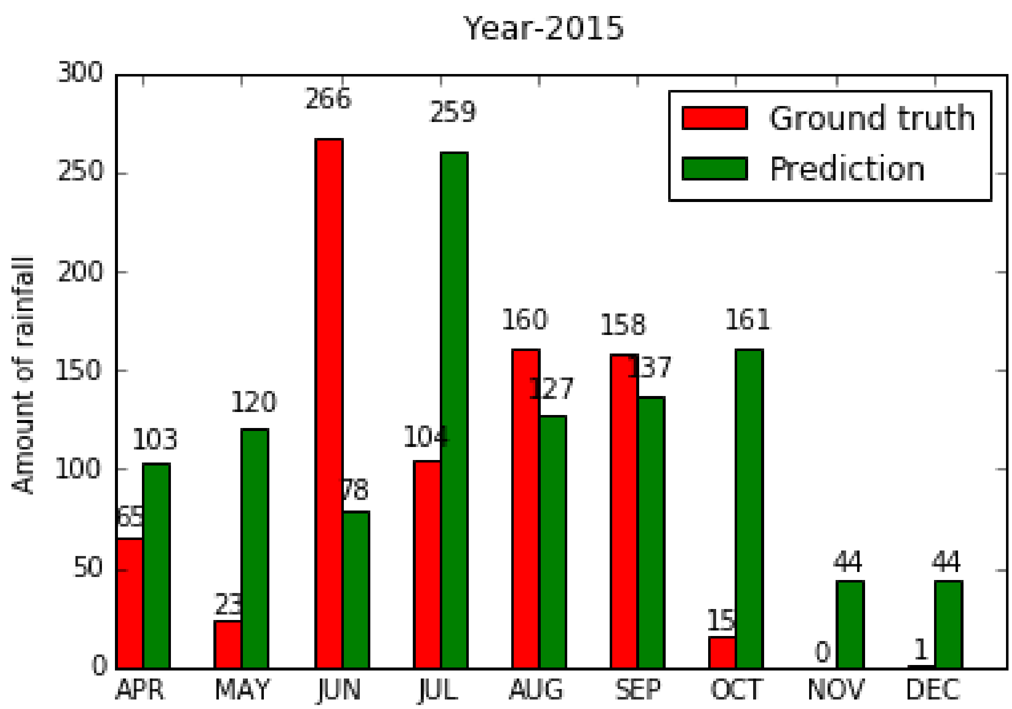
```
#2005 y_year_pred_2005 =
reg.predict(X_year_2005)

#2010
y_year_pred_2010 = reg.predict(X_year_2010)

#2015
y_year_pred_2015 = reg.predict(X_year_2015)
print "MEAN 2005"
print np.mean(y_year_2005),np.mean(y_year_pred_2005) print
"Standard deviation 2005"
print np.sqrt(np.var(y_year_2005)),np.sqrt(np.var(y_year_pred_2005))

print "MEAN 2010"
print np.mean(y_year_2010),np.mean(y_year_pred_2010) print
"Standard deviation 2010"
print np.sqrt(np.var(y_year_2010)),np.sqrt(np.var(y_year_pred_2010))

print "MEAN 2015"
print np.mean(y_year_2015),np.mean(y_year_pred_2015) print
"Standard deviation 2015"
print np.sqrt(np.var(y_year_2015)),np.sqrt(np.var(y_year_pred_2015))
plot_graphs(y_year_2005,y_year_pred_2005,"Year-2005")
plot_graphs(y_year_2010,y_year_pred_2010,"Year-2010")
plot_graphs(y_year_2015,y_year_pred_2015,"Year-2015")
```

```
MEAN 2005
121.2111111111111 134.68699821349824 Standard
deviation 2005
123.77066107608005 90.86310230416397
MEAN 2010
139.93333333333334 144.8050132651592
Standard deviation 2010
```

```
135.71320250194282  95.94931363601675  MEAN
2015
88.52222222222223 119.64752006738864
Standard deviation 2015
86.62446123324875 62.36355370163346
```








```
In [25]: #spliting training and testing data only for telangana telangana = np.asarray(data[['JAN',
         'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].loc[data['SUBDIVISION'] == 'TELANGANA'])
```

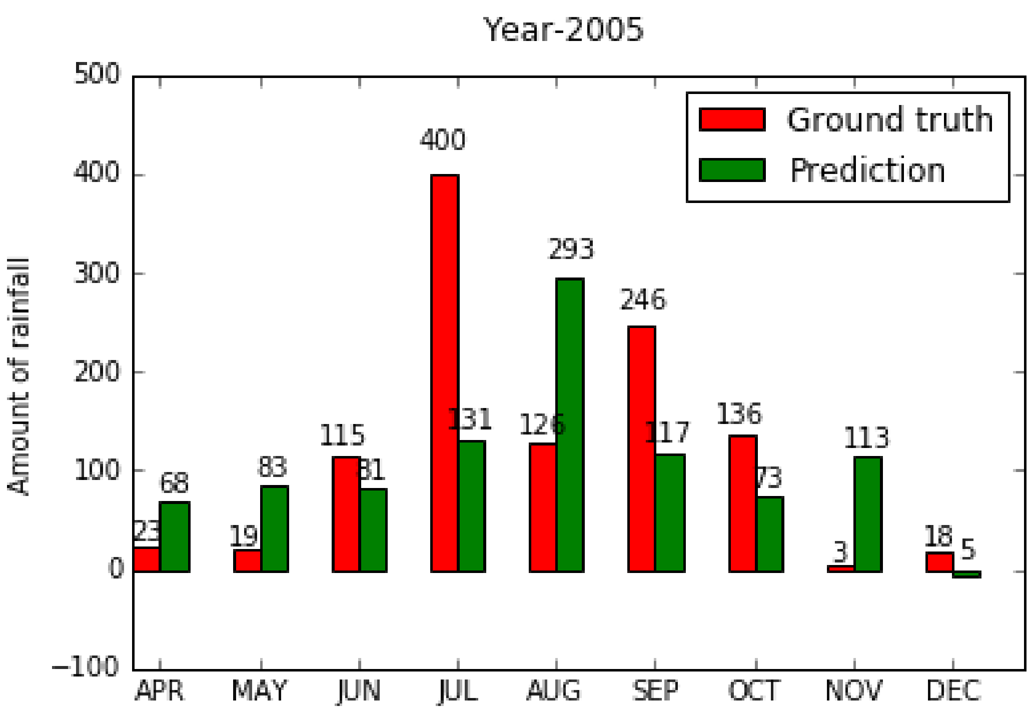
```
X = None; y = None for i in
range(telangana.shape[1]-3):
    if X is None:
        X = telangana[:, i:i+3] y
        = telangana[:, i+3]
    else:
        X = np.concatenate((X, telangana[:, i:i+3]), axis=0) y =
        np.concatenate((y, telangana[:, i+3]), axis=0)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.01, random_state=42)
```

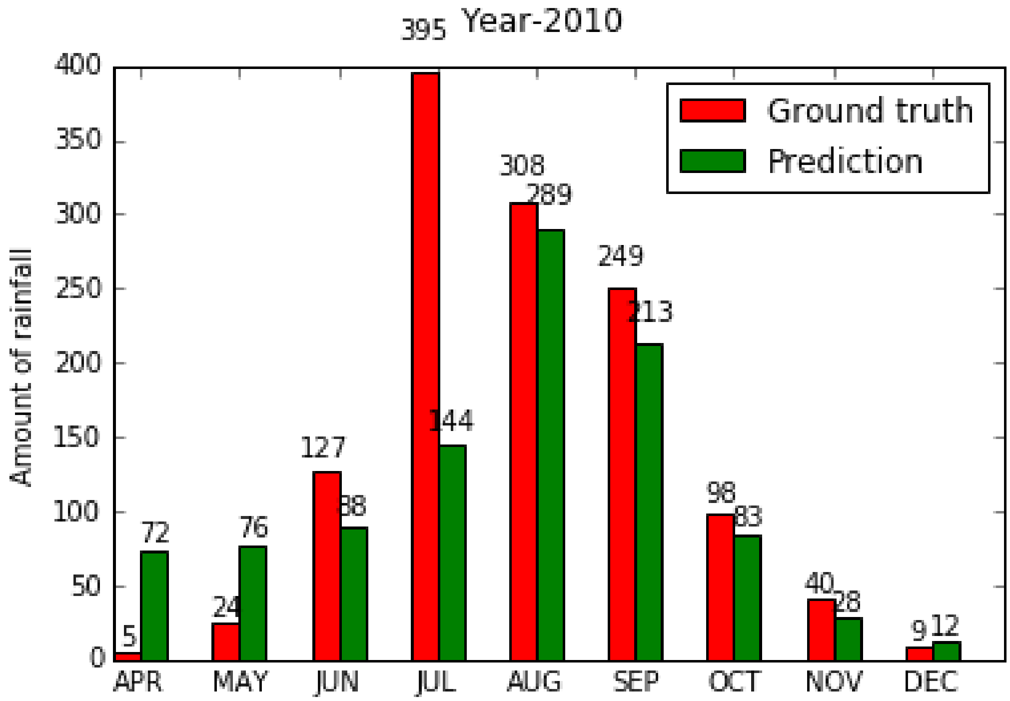
In [26]:
```
from sklearn import linear_model

# linear model reg =
linear_model.ElasticNet(alpha=0.5)
reg.fit(X_train, y_train) y_pred =
reg.predict(X_test)
print mean_absolute_error(y_test, y_pred)
```

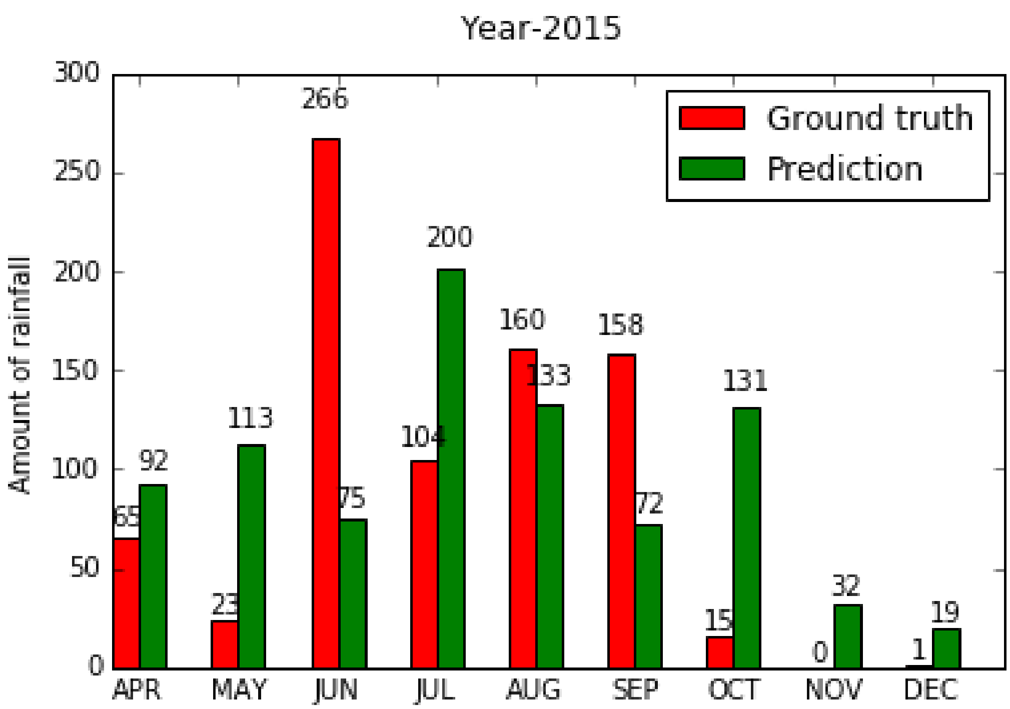
64.72601914484643

In [27]:
```
#2005
y_year_pred_2005 = reg.predict(X_year_2005)


#2010
y_year_pred_2010 = reg.predict(X_year_2010)

#2015
y_year_pred_2015 = reg.predict(X_year_2015)
print "MEAN 2005"
print np.mean(y_year_2005),np.mean(y_year_pred_2005) print
"Standard deviation 2005"
print np.sqrt(np.var(y_year_2005)),np.sqrt(np.var(y_year_pred_2005))


print "MEAN 2010"
print np.mean(y_year_2010),np.mean(y_year_pred_2010) print
"Standard deviation 2010"
print np.sqrt(np.var(y_year_2010)),np.sqrt(np.var(y_year_pred_2010))


print "MEAN 2015"
print np.mean(y_year_2015),np.mean(y_year_pred_2015) print
"Standard deviation 2015"
print np.sqrt(np.var(y_year_2015)),np.sqrt(np.var(y_year_pred_2015))
plot_graphs(y_year_2005,y_year_pred_2005,"Year-2005")
plot_graphs(y_year_2010,y_year_pred_2010,"Year-2010")
plot_graphs(y_year_2015,y_year_pred_2015,"Year-2015")
```

MEAN 2005
121.2111111111111 106.49798150231584 Standard deviation 2005
123.77066107608005 76.08558540019227
MEAN 2010
139.93333333333334 112.18662987131034
Standard deviation 2010
135.71320250194282 84.35813629737324
MEAN 2015
88.52222222222223 96.76817006572782 Standard deviation 2015
86.62446123324875 52.45304841713261







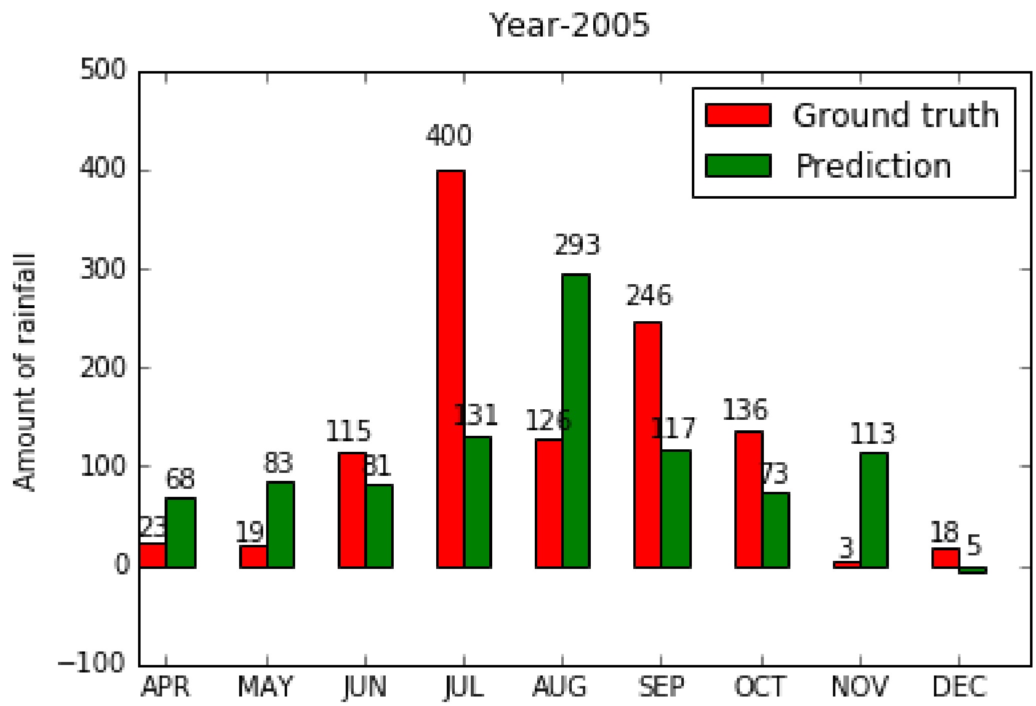

```
In [28]: from sklearn.svm import SVR

         # SVM model
```

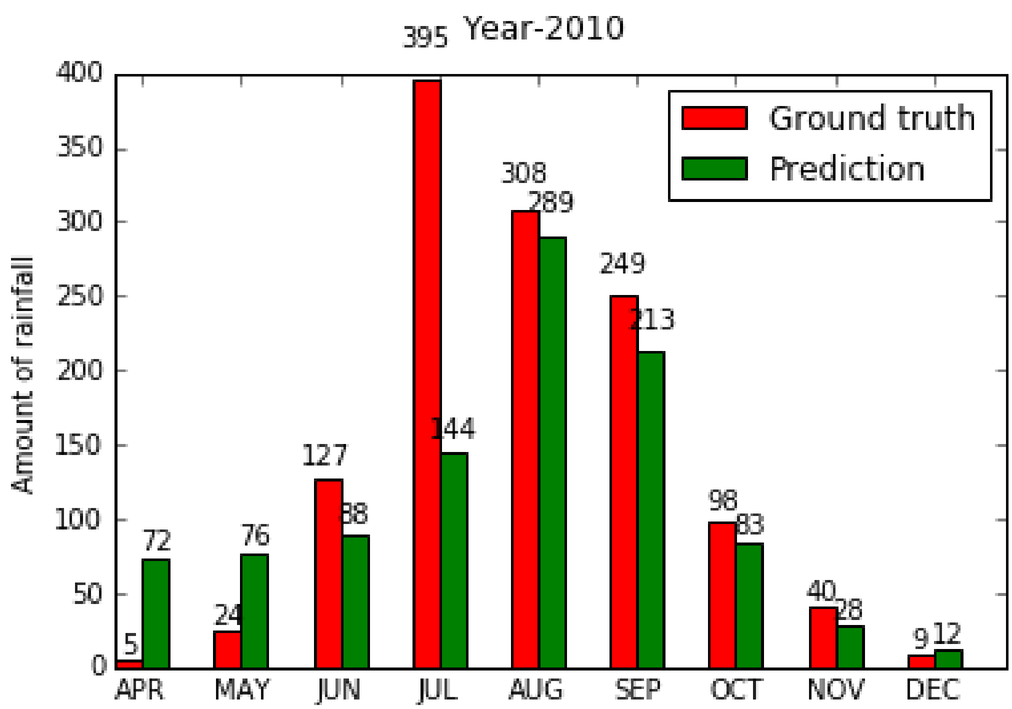
```
clf = SVR(kernel='rbf', gamma='auto', C=0.5, epsilon=0.2)
clf.fit(X_train, y_train) y_pred = clf.predict(X_test) print
mean_absolute_error(y_test, y_pred)
```

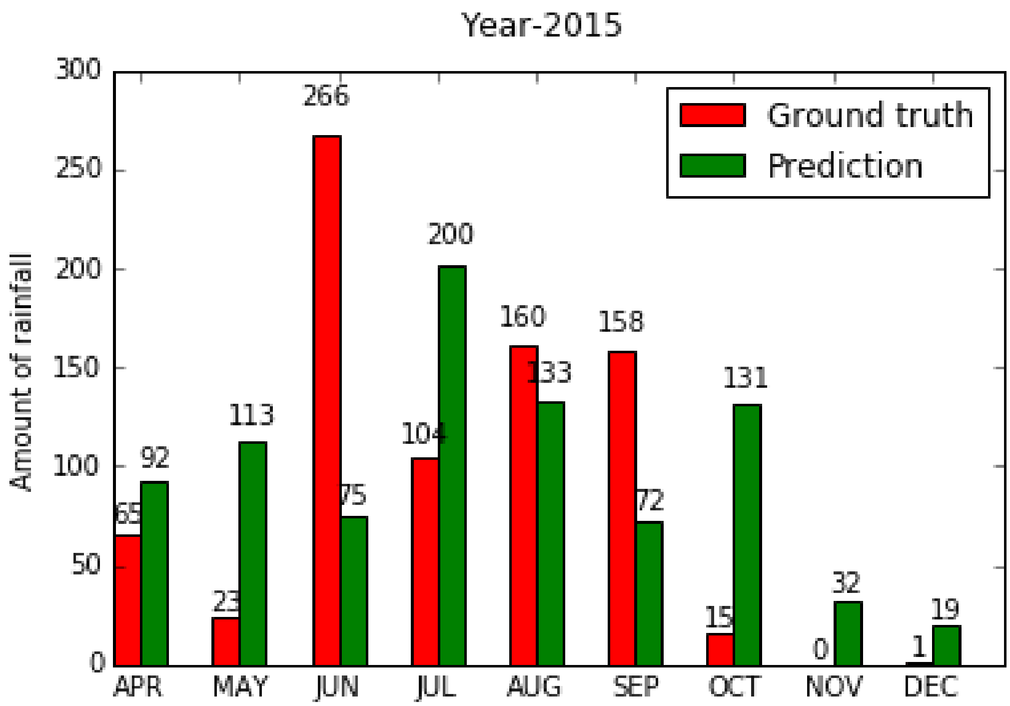
115.32415990638656

```
In [29]: #2005 y_year_pred_2005 =
reg.predict(X_year_2005)

#2010
y_year_pred_2010 = reg.predict(X_year_2010)

#2015
y_year_pred_2015 = reg.predict(X_year_2015)
print "MEAN 2005"
print np.mean(y_year_2005),np.mean(y_year_pred_2005) print
"Standard deviation 2005"
print np.sqrt(np.var(y_year_2005)),np.sqrt(np.var(y_year_pred_2005))

print "MEAN 2010"
print np.mean(y_year_2010),np.mean(y_year_pred_2010)
print "Standard deviation 2010"
print np.sqrt(np.var(y_year_2010)),np.sqrt(np.var(y_year_pred_2010))

print "MEAN 2015"
print np.mean(y_year_2015),np.mean(y_year_pred_2015) print
"Standard deviation 2015"
print np.sqrt(np.var(y_year_2015)),np.sqrt(np.var(y_year_pred_2015))
plot_graphs(y_year_2005,y_year_pred_2005,"Year-2005")
plot_graphs(y_year_2010,y_year_pred_2010,"Year-2010")
plot_graphs(y_year_2015,y_year_pred_2015,"Year-2015")
```

```
MEAN 2005
121.2111111111111 106.49798150231584 Standard
deviation 2005
123.77066107608005 76.08558540019227
MEAN 2010
139.93333333333334 112.18662987131034
Standard deviation 2010
135.71320250194282 84.35813629737324
MEAN 2015
88.52222222222223 96.76817006572782 Standard
deviation 2015
86.62446123324875 52.45304841713261
```


Year-2005
Amount of rainfall
500
400
300
200
100
0
−100
Ground truth
Prediction
23
68
19
83
115
81
400
131
126
293
246
117
136
73
3
113
18
5
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC


Year-2010
Amount of rainfall
400
350
300
250
200
150
100
50
0
Ground truth
Prediction
5
72
24
76
127
88
395
144
308
289
249
213
98
83
40
28
9
12
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC

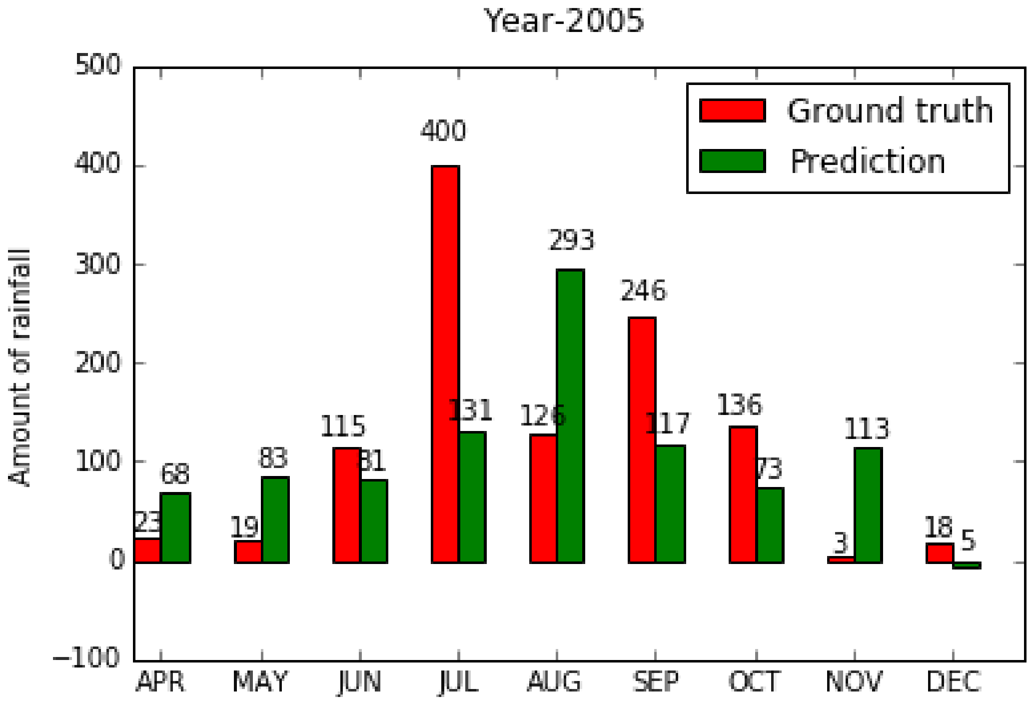


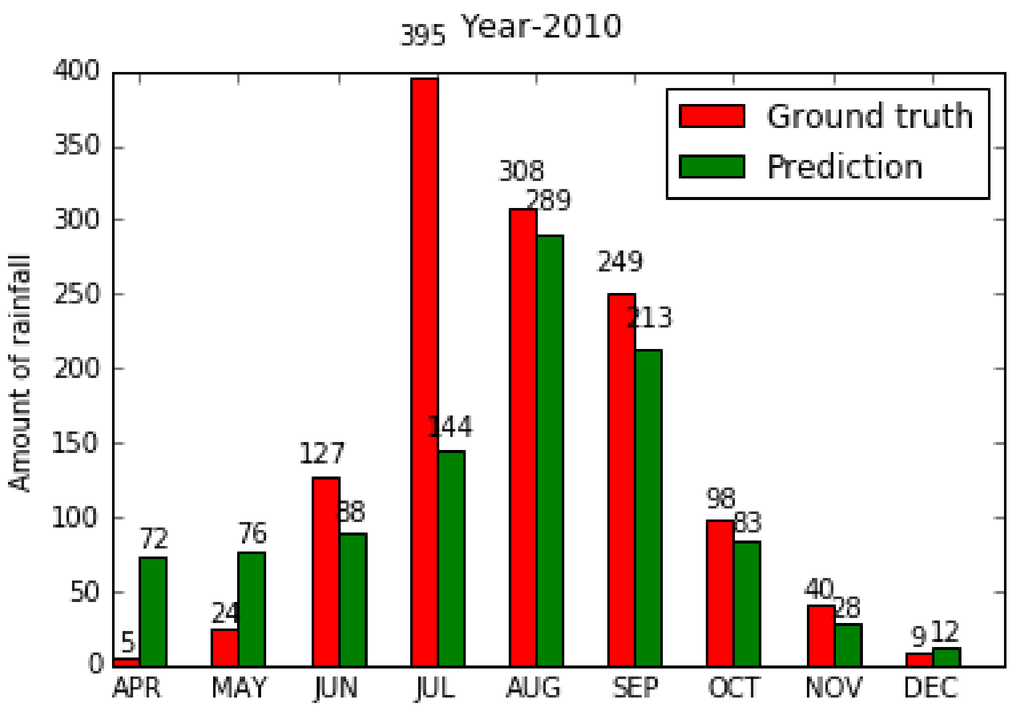

```
In [30]: model.fit(x=np.expand_dims(X_train, axis=2), y=y_train, batch_size=64, epochs=10, verbose=1, v
y_pred = model.predict(np.expand_dims(X_test, axis=2)) print mean_absolute_error(y_test, y_pred)

Train on 921 samples, validate on 103 samples Epoch
1/10
921/921 [==============================] - 0s 66us/step - loss: 7274.9487 - mean_absolute_error: 63.502
Epoch 2/10
921/921 [==============================] - 0s 56us/step - loss: 6431.8426 - mean_absolute_error: 56.767
Epoch 3/10
921/921 [==============================] - 0s 56us/step - loss: 6046.0127 - mean_absolute_error: 58.486
Epoch 4/10

921/921 [==============================] - 0s 56us/step - loss: 5883.5181 - mean_absolute_error: 56.438
Epoch 5/10
921/921 [==============================] - 0s 57us/step - loss: 5764.2698 - mean_absolute_error: 55.178
Epoch 6/10
921/921 [==============================] - 0s 55us/step - loss: 5706.7510 - mean_absolute_error: 55.346
Epoch 7/10
921/921 [==============================] - 0s 56us/step - loss: 5636.2414 - mean_absolute_error: 54.452
Epoch 8/10
921/921 [==============================] - 0s 57us/step - loss: 5564.0726 - mean_absolute_error: 54.566
Epoch 9/10
921/921 [==============================] - 0s 57us/step - loss: 5529.6288 - mean_absolute_error: 54.002
Epoch 10/10
```

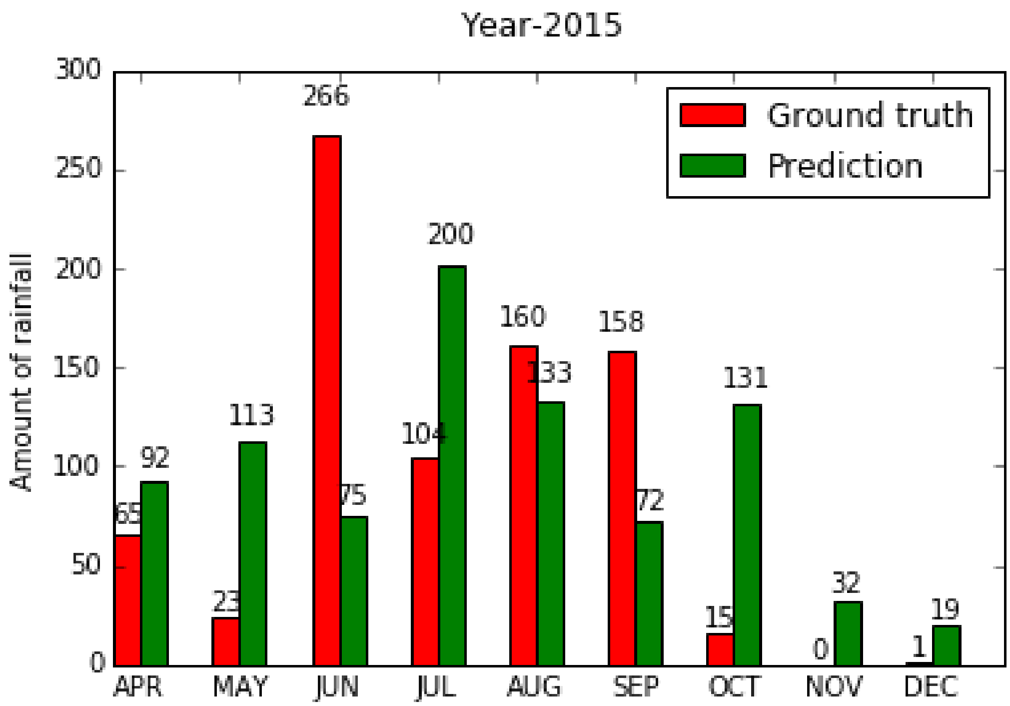
```
921/921 [==============================] - 0s 57us/step - loss: 5478.9296 - mean_absolute_error: 53.525

 65.82400645938786
```

```
In [31]: #2005
          y_year_pred_2005 = reg.predict(X_year_2005)

         #2010
         y_year_pred_2010 = reg.predict(X_year_2010)

         #2015
         y_year_pred_2015 = reg.predict(X_year_2015)
print "MEAN 2005"
         print  np.mean(y_year_2005),np.mean(y_year_pred_2005)  print
         "Standard deviation 2005"
         print np.sqrt(np.var(y_year_2005)),np.sqrt(np.var(y_year_pred_2005))

         print          "MEAN          2010"          print
         np.mean(y_year_2010),np.mean(y_year_pred_2010)   print
         "Standard deviation 2010"
         print np.sqrt(np.var(y_year_2010)),np.sqrt(np.var(y_year_pred_2010))

         print "MEAN 2015"
         print  np.mean(y_year_2015),np.mean(y_year_pred_2015)  print
         "Standard deviation 2015"
         print np.sqrt(np.var(y_year_2015)),np.sqrt(np.var(y_year_pred_2015))
plot_graphs(y_year_2005,y_year_pred_2005,"Year-2005")
         plot_graphs(y_year_2010,y_year_pred_2010,"Year-2010")
         plot_graphs(y_year_2015,y_year_pred_2015,"Year-2015")
```

```
MEAN 2005
121.2111111111111  106.49798150231584  Standard
deviation 2005
123.77066107608005 76.08558540019227
MEAN 2010
139.93333333333334 112.18662987131034
Standard deviation 2010
135.71320250194282 84.35813629737324
MEAN 2015
88.52222222222223  96.76817006572782  Standard
deviation 2015
86.62446123324875 52.45304841713261
```


Year-2005
Ground truth
Prediction
Amount of rainfall
500
400
300
200
100
0
−100
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
23
68
19
83
115
81
400
131
126
293
246
117
136
73
3
113
18
5


Year-2010
Ground truth
Prediction
Amount of rainfall
400
350
300
250
200
150
100
50
0
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
5
72
24
76
127
88
395
144
308
289
249
213
98
83
40
28
9
12



1.12 Prediction Observations

1.12.1 Training on complete dataset

Algorithm	MAE
Linear Regression	94.94821727619338
SVR	127.74073860203839
Artificial neural nets	85.2648713528865

1.12.2 Training on telangana dataset

Algorithm	MAE
Linear Regression	70.61463829282977
SVR	90.30526775954294
Artificial neural nets	59.95190786532157

- Neural Networks performs better than SVR etc.
- Observed MAE is very high which indicates machine learning models won’t work well for prediction of rainfall.
- Telangana data has a single pattern that can be learned by models, rather than learning different patterns of all states. so has high accuracy.
- Analysed individual year rainfall patterns for 2005, 2010, 2015.
- Approximately close means, noticed less standard deviations.

1.13 District wise details

- Similar to above the number of attributes is same, we don’t have year in this.
- The amount of rainfall in mm for each district is added from 1950-2000.

- We analyse the data individually for the state **Andhra Pradesh**

```
In [32]: district = pd.read_csv("../data/district_wise_rainfall_normal.csv",sep=",") district
         = district.fillna(district.mean()) district.info()
```

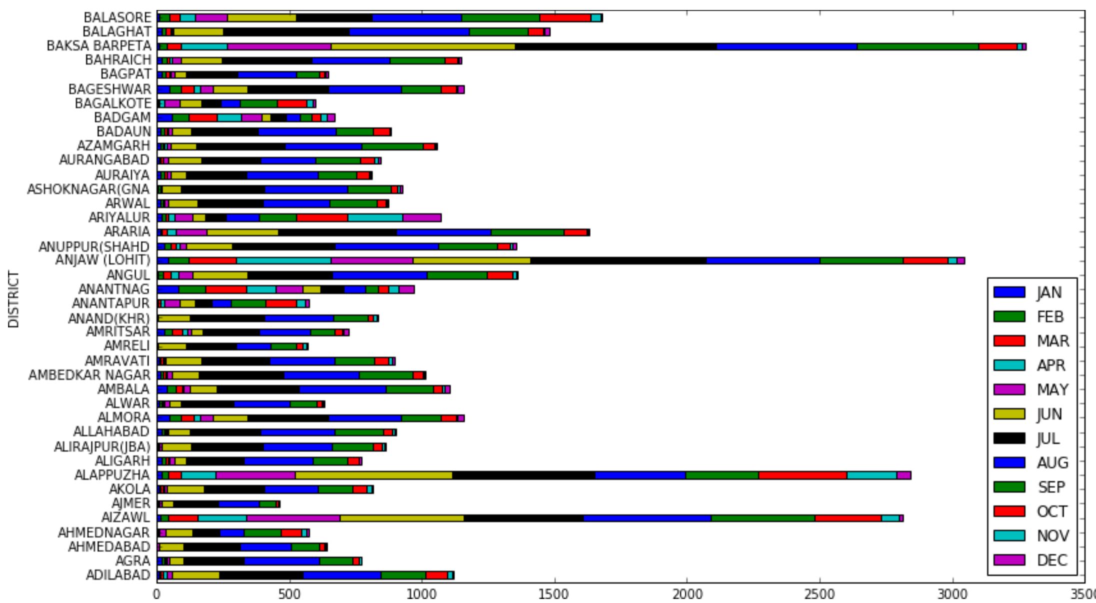
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 641 entries, 0 to 640 Data
columns (total 19 columns):
STATE_UT_NAME 641 non-null object
DISTRICT         641 non-null object
JAN              641 non-null float64
FEB              641 non-null float64
MAR              641 non-null float64
APR              641 non-null float64
MAY              641 non-null float64
JUN              641 non-null float64
JUL              641 non-null float64
AUG              641 non-null float64
SEP              641 non-null float64
OCT              641 non-null float64
NOV              641 non-null float64
DEC              641 non-null float64
ANNUAL           641 non-null float64
Jan-Feb          641 non-null float64
Mar-May          641 non-null float64
Jun-Sep     641    non-null    float64    Oct-Dec
    641 non-null float64
dtypes:  float64(17),  object(2)  memory
usage: 95.2+ KB
```

```
In [33]: district.head()
```

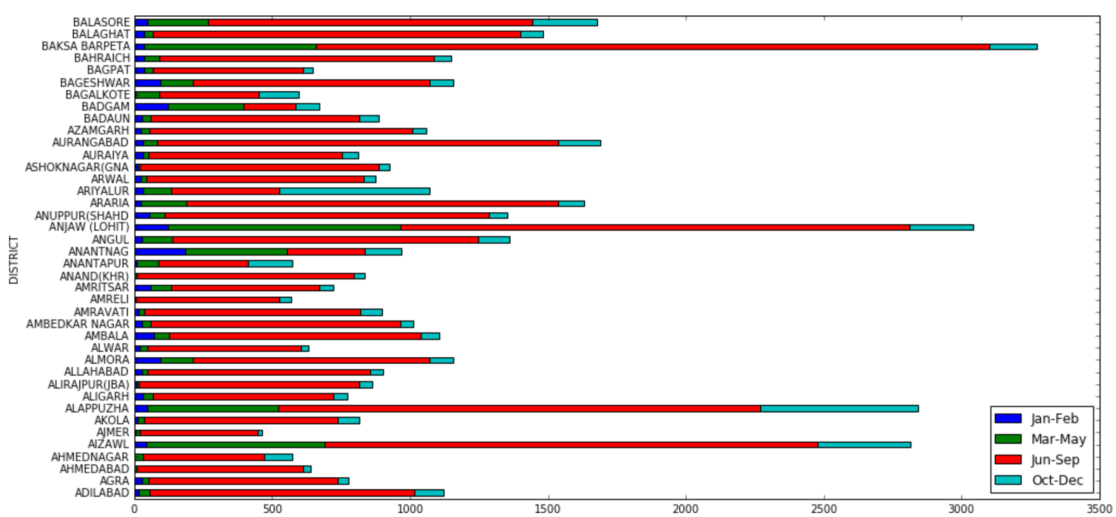
```
Out[33]:                     STATE_UT_NAME              DISTRICT JAN FEB MAR APR \
0           ANDAMAN And NICOBAR ISLANDS       NICOBAR 107.3 57.9 65.2 117.0
1           ANDAMAN And NICOBAR ISLANDS SOUTH ANDAMAN 43.7 26.0 18.6 90.5
2           ANDAMAN And NICOBAR ISLANDS N & M ANDAMAN 32.7 15.9 8.6 53.4
3           ARUNACHAL PRADESH   LOHIT 42.2 80.8 176.4 358.5
4           ARUNACHAL PRADESH   EAST SIANG 33.3 79.5 105.9 216.5


                           MAY JUN JUL AUG SEP OCT NOV DEC ANNUAL Jan-Feb \
         0  358.5 295.5 285.0 271.9 354.8 326.0 315.2 250.9 2805.2 165.2
         1  374.4 457.2 421.3 423.1 455.6 301.2 275.8 128.3 3015.7   69.7
         2  343.6 503.3 465.4 460.9 454.8 276.1 198.6 100.0 2913.3   48.6
         3  306.4 447.0 660.1 427.8 313.6 167.1 34.1 29.8 3043.8 123.0
         4  323.0 738.3 990.9 711.2 568.0 206.9 29.5 31.7 4034.7 112.8


            Mar-May Jun-Sep Oct-Dec
         0 540.7 1207.2   892.1   1  483.5
1757.2 705.3
```

```
2       405.6  1884.4  574.7
3       841.3  1848.5  231.0
4       645.4  3008.4  268.1
```

```
In [34]: district[['DISTRICT', 'JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                                          'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].groupby("DISTRICT").mean()[:40].plot.barh(stacked=T
```




```
In [35]: district[['DISTRICT', 'Jan-Feb', 'Mar-May',
                                  'Jun-Sep', 'Oct-Dec']].groupby("DISTRICT").sum()[:40].plot.barh(stacked=True,figsize=(1
```



1.14 Observations

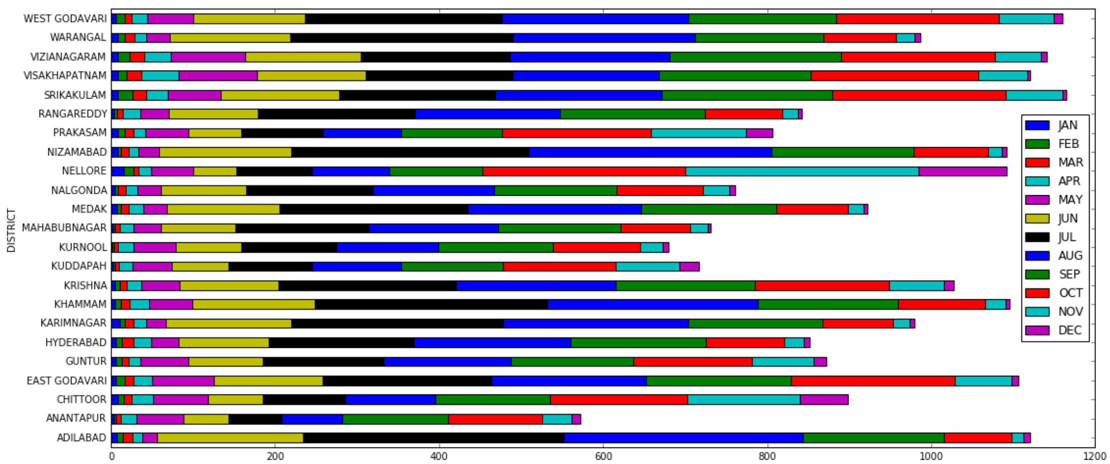
- The above two graphs shows the distribution of over each district.
- As there are large number of districts only 40 were shown in the graphs.

0

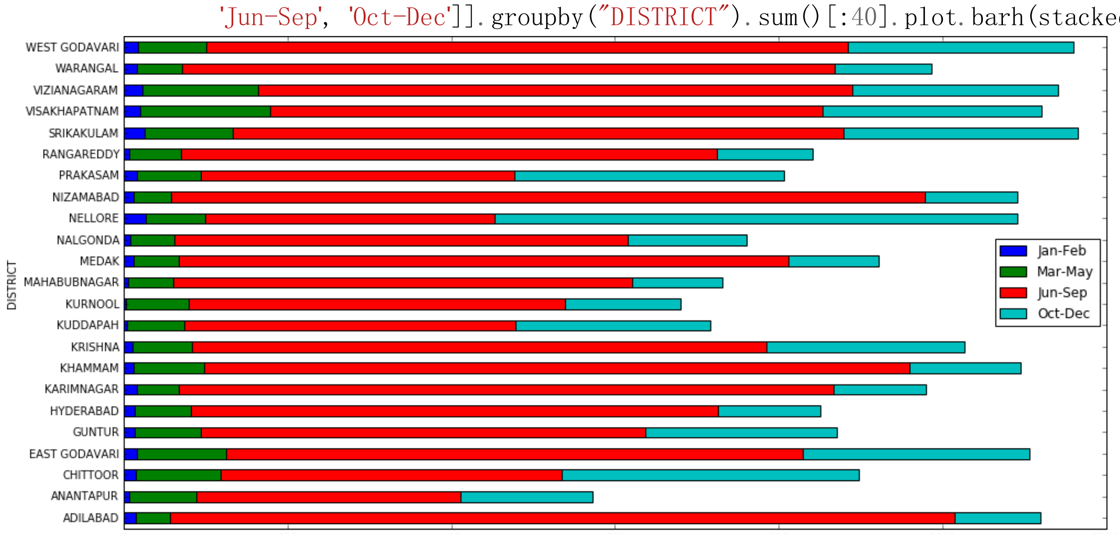
Andhra Pradesh Data

```
In [36]: ap_data = district[district['STATE_UT_NAME'] == 'ANDHRA PRADESH']
```

```
In [37]: ap_data[['DISTRICT', 'JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                  'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].groupby("DISTRICT").mean()[:40].plot.barh(stacked=T
```




```
In [38]: ap_data[['DISTRICT', 'Jan-Feb', 'Mar-May',
                  'Jun-Sep', 'Oct-Dec']].groupby("DISTRICT").sum()[:40].plot.barh(stacked=True,figsize=(1
```

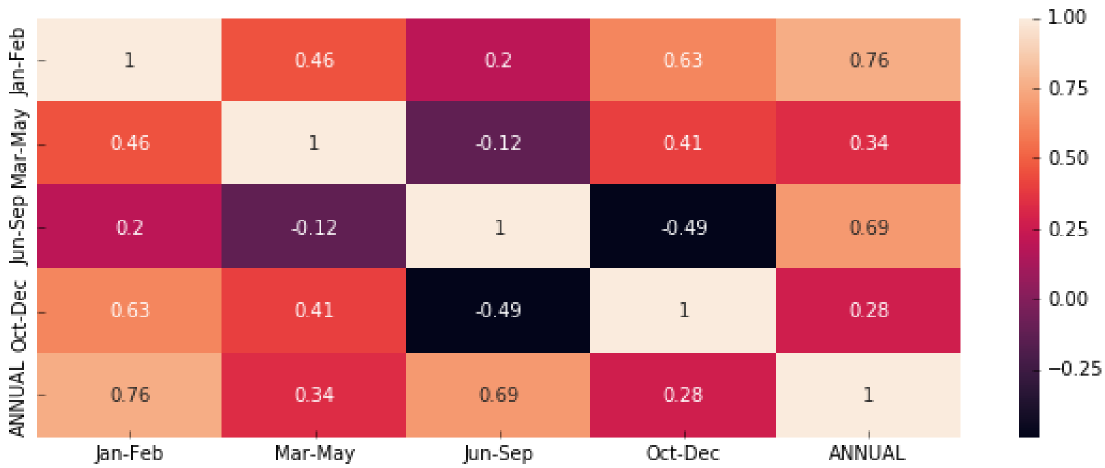


1.15 Observations

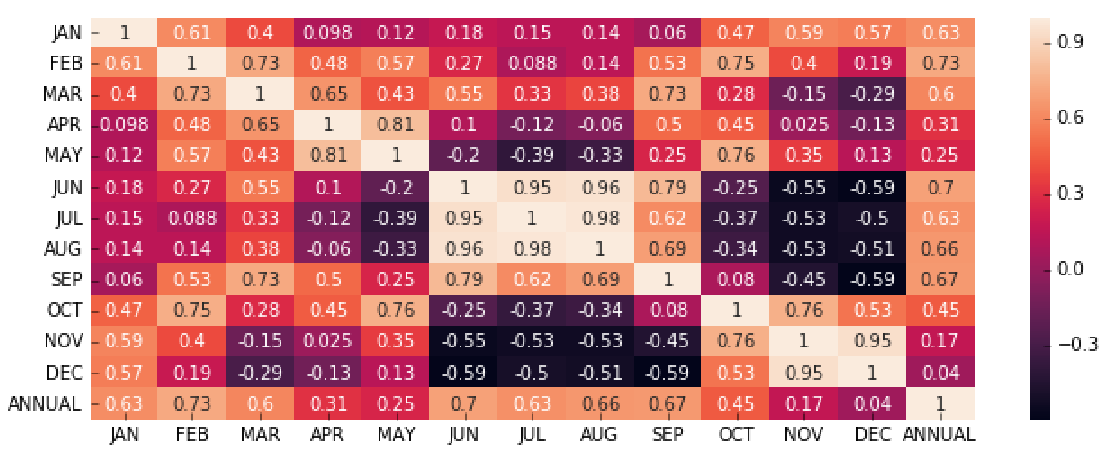
- The above two graphs shows the distribution of over each district in **Andhra Pradesh.**
- The above graphs show that more amount of rainfall is found in srikakulam district, least amount of rainfall is found in Anantapur district.

- It also shows that almost all states have more amount of rainfall have more amount of rainfall in the months june, july, september.

```
In [39]: plt.figure(figsize=(11,4)) sns.heatmap(ap_data[['Jan-Feb','Mar-May','Jun-Sep','Oct-
         Dec','ANNUAL']].corr(),annot=True) plt.show()
```




```
In [40]: plt.figure(figsize=(11,4))
         sns.heatmap(ap_data[['JAN','FEB','MAR','APR','MAY','JUN','JUL','AUG','SEP','OCT','NOV','DEC',' plt.show()
```



1.16 Observations

- It is observed that in **Andhra Pradesh**, annual rainfall depends more in the months of january, febuary.
- It also shows that if there is rainfall in months march, april, may then there is less amount of rainfall in the months june, july, august, september.

1.17 Predictions

- We used the same types of models and evaluation metrics used for the above dataset.
- We also tested the amount of rainfall in hyderabad by models trained on complete dataset and andhra pradesh dataset.

In [41]:
```
# testing and training for the complete data from
sklearn.model_selection import train_test_split from
sklearn.metrics import mean_absolute_error
division_data = np.asarray(district[['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG', 'SEP', 'OCT',
'NOV', 'DEC']])

X = None; y = None for i in
range(division_data.shape[1]-3):
    if X is None:
        X = division_data[:, i:i+3] y
        = division_data[:, i+3]
    else:
        X = np.concatenate((X, division_data[:, i:i+3]), axis=0) y =
        np.concatenate((y, division_data[:, i+3]), axis=0)


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [42]:
```
temp = district[['DISTRICT','JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL','AUG', 'SEP', 'OCT hyd =
 np.asarray(temp[['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL','AUG', 'SEP', 'OCT', 'N
# print temp
X_year = None; y_year = None for i
in range(hyd.shape[1]-3):
    if X_year is None:
        X_year = hyd[:, i:i+3] y_year
        = hyd[:, i+3]
    else:
        X_year = np.concatenate((X_year, hyd[:, i:i+3]), axis=0) y_year =
        np.concatenate((y_year, hyd[:, i+3]), axis=0)
```

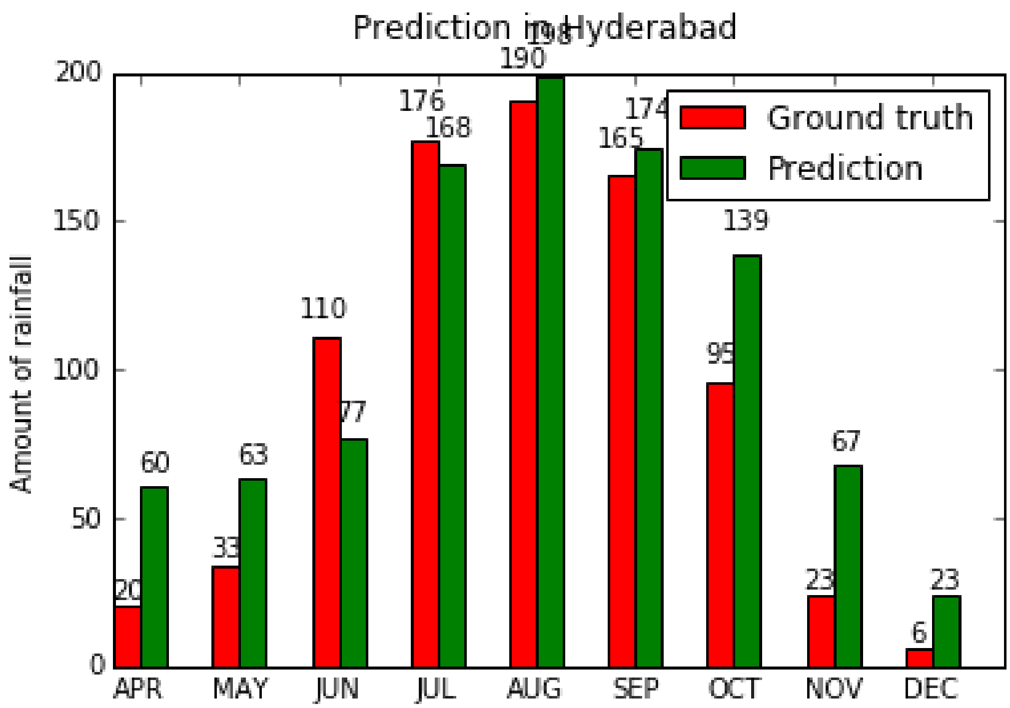
In [43]:
```
from sklearn import linear_model

# linear model reg =
linear_model.ElasticNet(alpha=0.5)
reg.fit(X_train, y_train) y_pred =
reg.predict(X_test) print
mean_absolute_error(y_test, y_pred)
```

57.08862331011236

In [44]:
```
y_year_pred = reg.predict(X_year) print "MEAN
Hyderabad" print
np.mean(y_year),np.mean(y_year_pred) print
"Standard deviation hyderabad"
```

```
print                                              np.sqrt(np.var(y_year)),np.sqrt(np.var(y_year_pred))

plot_graphs(y_year,y_year_pred,"Prediction in Hyderabad")
```

```
MEAN Hyderabad
91.48888888888888 108.20250522332894
Standard deviation hyderabad
69.2514651982091 58.90326979488754
```

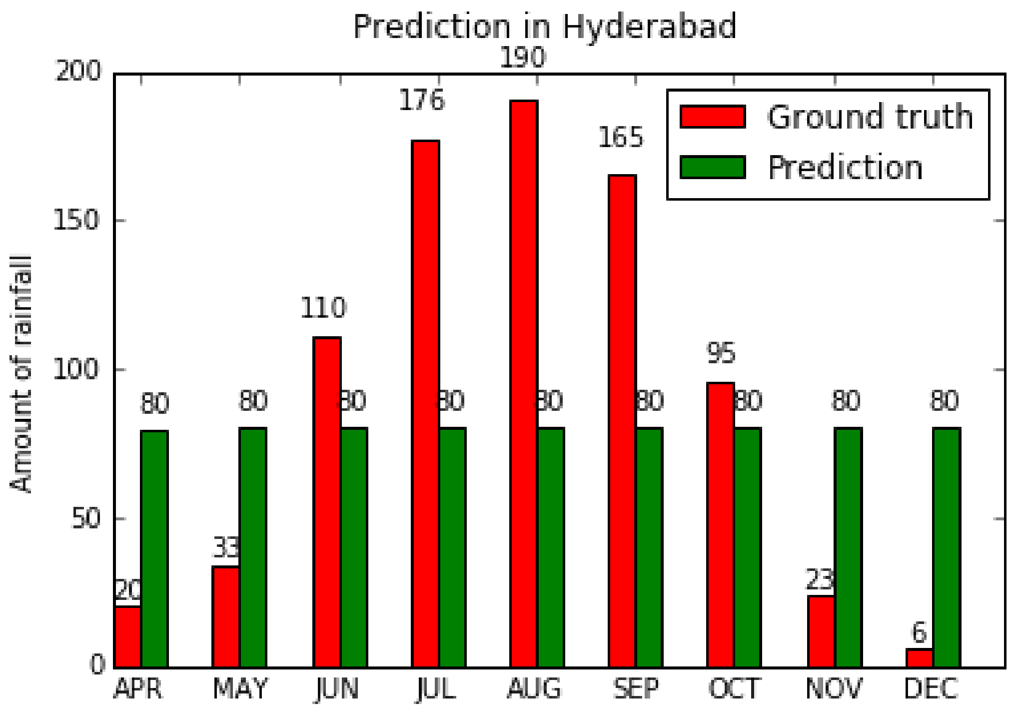


In [45]:
```
from sklearn.svm import SVR

# SVM model clf  =  SVR(gamma='auto',  C=0.1,
epsilon=0.2) clf.fit(X_train, y_train) y_pred
=          clf.predict(X_test)          print
mean_absolute_error(y_test, y_pred)
```

```
116.60671510825178
```

In [46]:
```
y_year_pred = clf.predict(X_year) print "MEAN
Hyderabad"                                print
np.mean(y_year),np.mean(y_year_pred)   print
"Standard deviation hyderabad"
print                                              np.sqrt(np.var(y_year)),np.sqrt(np.var(y_year_pred))

plot_graphs(y_year,y_year_pred,"Prediction in Hyderabad")
```

```
MEAN Hyderabad
91.48888888888888 80.34903236716154
Standard deviation hyderabad
69.2514651982091 0.14736007434982146
```



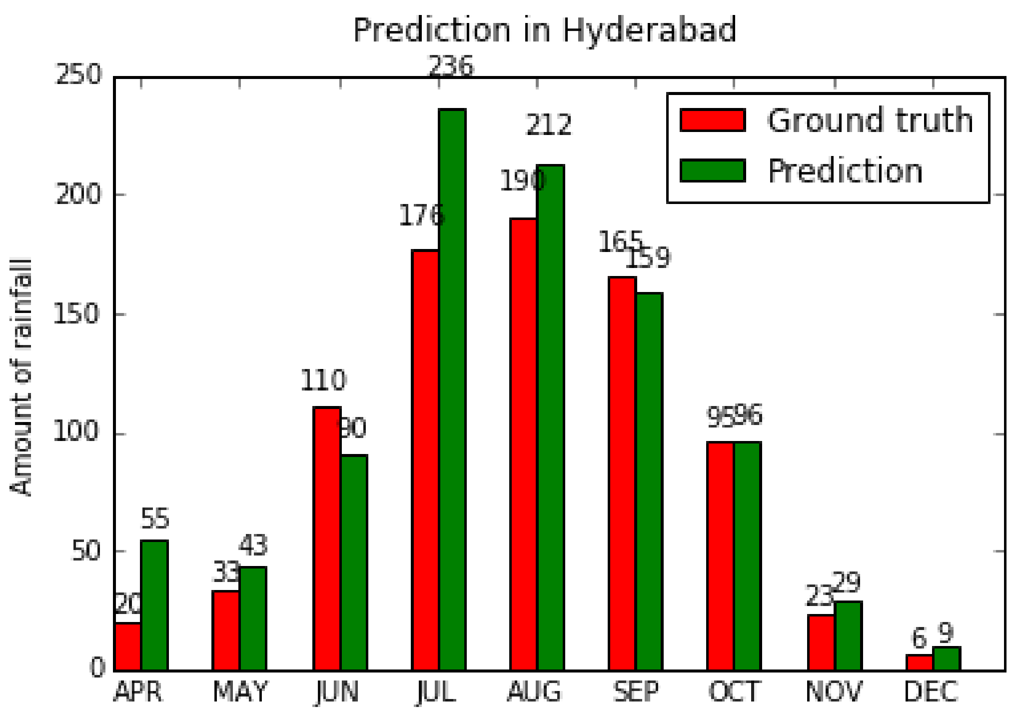
In [47]:
```
model.fit(x=np.expand_dims(X_train, axis=2), y=y_train, batch_size=64, epochs=10, verbose=1, v
y_pred = model.predict(np.expand_dims(X_test, axis=2)) print mean_absolute_error(y_test, y_pred)
```

```
Train on 4153 samples, validate on 462 samples
Epoch 1/10
4153/4153 [==============================] - 0s 57us/step - loss: 6957.2028 - mean_absolute_error: 50.9
Epoch 2/10
4153/4153 [==============================] - 0s 78us/step - loss: 5258.5688 - mean_absolute_error: 43.7
Epoch 3/10
4153/4153 [==============================] - 0s 56us/step - loss: 5122.4481 - mean_absolute_error: 42.5
Epoch 4/10
4153/4153 [==============================] - 0s 54us/step - loss: 5036.6459 - mean_absolute_error: 42.0
Epoch 5/10
4153/4153 [==============================] - 0s 53us/step - loss: 4964.9985 - mean_absolute_error: 41.4
Epoch 6/10
4153/4153 [==============================] - 0s 54us/step - loss: 5006.1478 - mean_absolute_error: 41.7
Epoch 7/10
4153/4153 [==============================] - 0s 54us/step - loss: 4917.7239 - mean_absolute_error: 41.2
Epoch 8/10
4153/4153 [==============================] - 0s 55us/step - loss: 4861.6742 - mean_absolute_error: 41.1
Epoch 9/10
4153/4153 [==============================] - 0s 55us/step - loss: 4792.0339 - mean_absolute_error: 40.5
Epoch 10/10
```

```
4153/4153 [==============================] - 0s 54us/step - loss: 4796.9758 - mean_absolute_error: 40.5
42.14205056426844
```

```
In [48]: y_year_pred = model.predict(np.expand_dims(X_year, axis=2))
         print "MEAN Hyderabad" print
         np.mean(y_year),np.mean(y_year_pred) print "Standard
         deviation hyderabad"
         print np.sqrt(np.var(y_year)),np.sqrt(np.var(y_year_pred))


         plot_graphs(y_year,y_year_pred,"Prediction in Hyderabad")
```

```
MEAN Hyderabad
91.48888888888888 103.67171
Standard deviation hyderabad
69.2514651982091 76.83028
```




```
In [49]: # training and testing sets for only andhra pradesh data from
         sklearn.model_selection import train_test_split from
         sklearn.metrics import mean_absolute_error
division_data = np.asarray(ap_data[['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG', 'SEP', 'OCT', 'NOV',
         'DEC']])
```

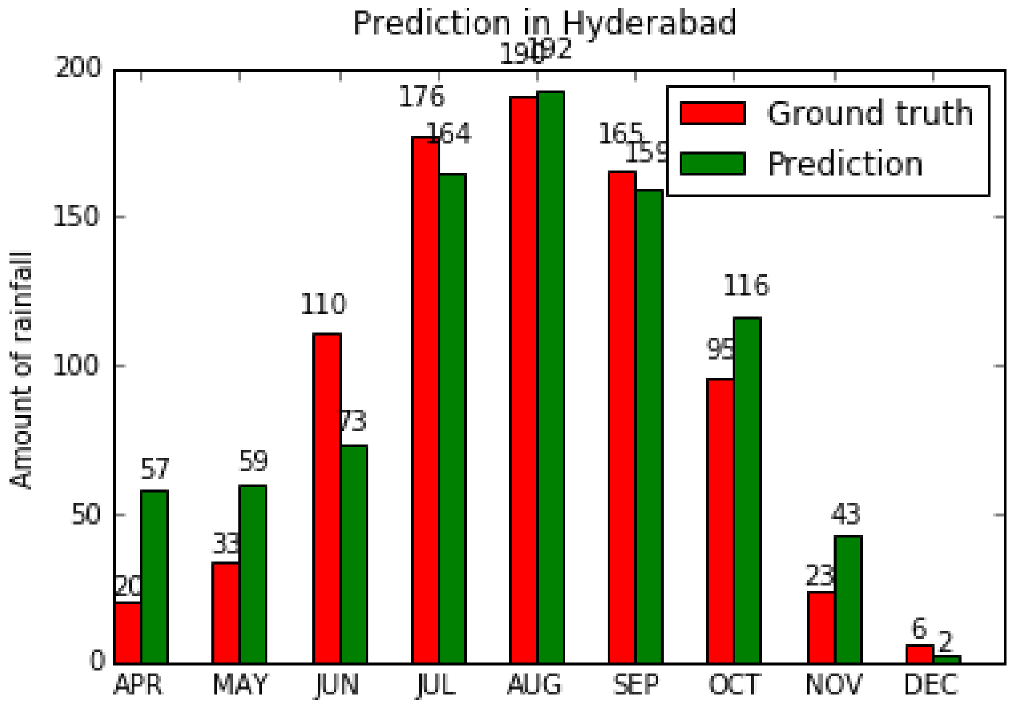
```
X = None; y = None for i in
range(division_data.shape[1]-3):
    if X is None:
        X = division_data[:, i:i+3] y
        = division_data[:, i+3]
    else:
        X = np.concatenate((X, division_data[:, i:i+3]), axis=0) y =
        np.concatenate((y, division_data[:, i+3]), axis=0)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [50]:
```
from sklearn import linear_model

# linear model reg =
linear_model.ElasticNet(alpha=0.5)
reg.fit(X_train, y_train) y_pred =
reg.predict(X_test) print
mean_absolute_error(y_test, y_pred)
```

31.249748674622477

In [51]:
```
y_year_pred = reg.predict(X_year) print "MEAN Hyderabad" print
np.mean(y_year),np.mean(y_year_pred) print "Standard
deviation hyderabad" print
np.sqrt(np.var(y_year)),np.sqrt(np.var(y_year_pred))
plot_graphs(y_year,y_year_pred,"Prediction in Hyderabad")
```

MEAN Hyderabad
91.48888888888888 96.54891993068443
Standard deviation hyderabad
69.2514651982091 60.819355195446896

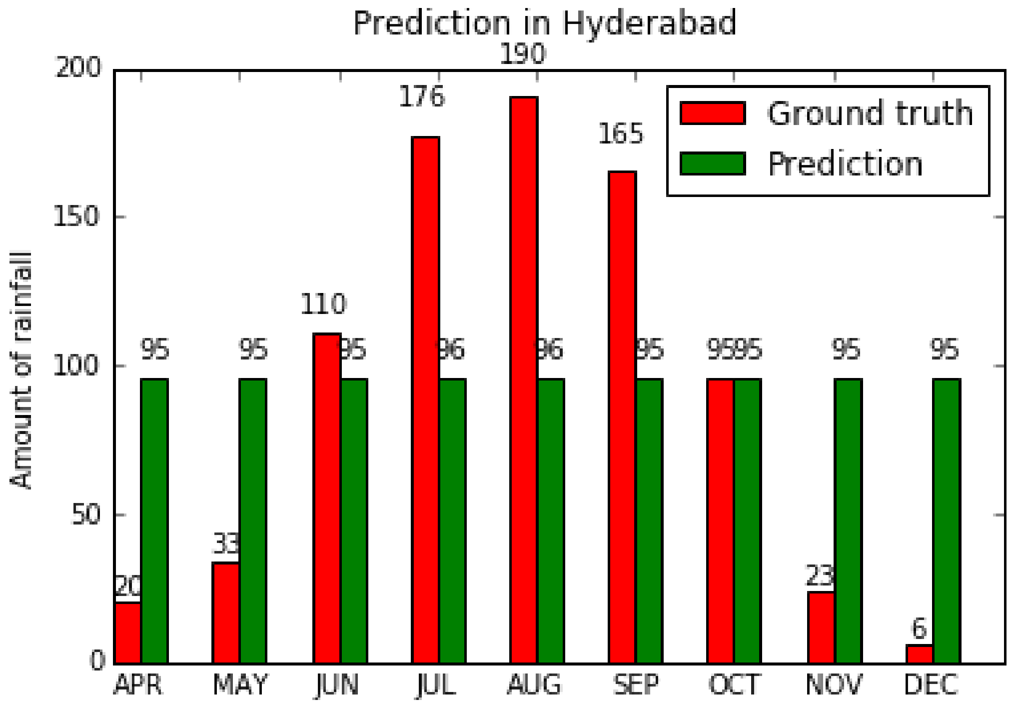



```
In [52]: from sklearn.svm import SVR

         # SVM model clf  =  SVR(gamma='auto',  C=0.1,
         epsilon=0.2) clf.fit(X_train, y_train) y_pred
         =          clf.predict(X_test)          print
         mean_absolute_error(y_test, y_pred)
```

59.35057496896855

```
In [53]: y_year_pred = clf.predict(X_year) print
         "MEAN Hyderabad"
         print  np.mean(y_year),np.mean(y_year_pred)  print
         "Standard deviation hyderabad"
         print                                        np.sqrt(np.var(y_year)),np.sqrt(np.var(y_year_pred))
         plot_graphs(y_year,y_year_pred,"Prediction in Hyderabad") MEAN Hyderabad
```

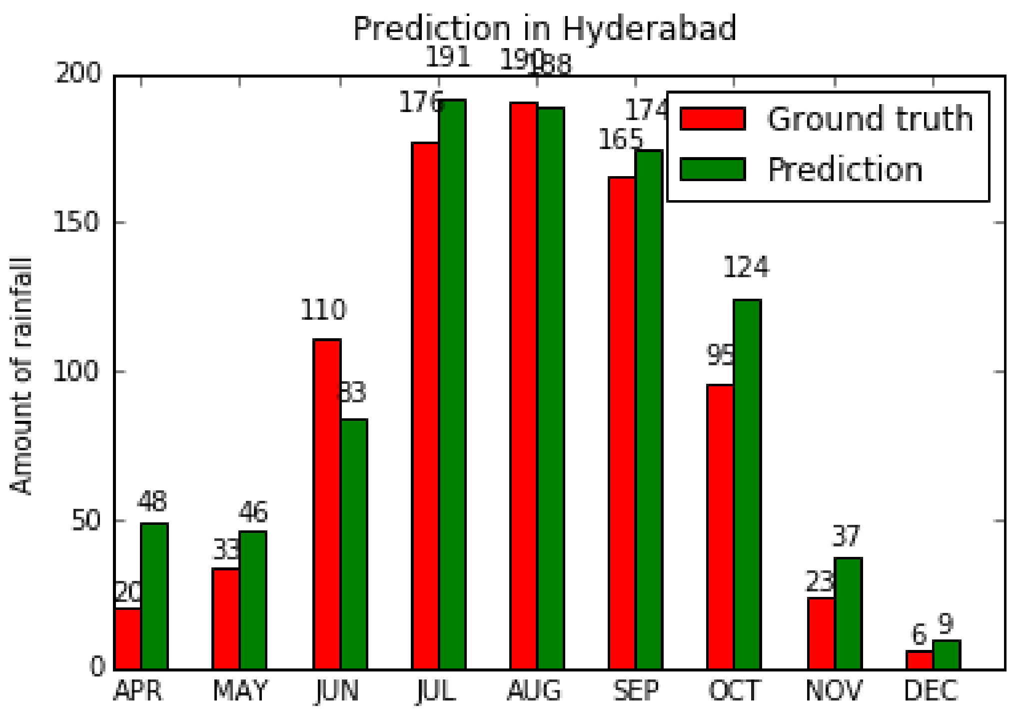
91.48888888888888 95.89978206795146
Standard deviation hyderabad
69.2514651982091 0.09247315036320868




```
In [54]: model.fit(x=np.expand_dims(X_train, axis=2), y=y_train, batch_size=64, epochs=10, verbose=1, v
         y_pred = model.predict(np.expand_dims(X_test, axis=2)) print mean_absolute_error(y_test, y_pred)

Train on 148 samples, validate on 17 samples
Epoch 1/10
148/148 [==============================] - 0s 120us/step - loss: 1778.6490 - mean_absolute_error: 30.94 Epoch
2/10
148/148 [==============================] - 0s 91us/step - loss: 1664.5006 - mean_absolute_error: 29.980
Epoch 3/10
148/148 [==============================] - 0s 92us/step - loss: 1504.4134 - mean_absolute_error: 28.078
Epoch 4/10
148/148 [==============================] - 0s 89us/step - loss: 1405.6685 - mean_absolute_error: 26.989
Epoch 5/10
148/148 [==============================] - 0s 84us/step - loss: 1399.6531 - mean_absolute_error: 26.840
Epoch 6/10
148/148 [==============================] - 0s 83us/step - loss: 1364.1109 - mean_absolute_error: 26.374
Epoch 7/10
148/148 [==============================] - 0s 79us/step - loss: 1321.5538 - mean_absolute_error: 26.143
Epoch 8/10
148/148 [==============================] - 0s 83us/step - loss: 1302.3495 - mean_absolute_error: 26.044 Epoch
9/10
148/148 [==============================] - 0s 81us/step - loss: 1290.8667 - mean_absolute_error: 25.858
Epoch 10/10
148/148 [==============================] - 0s 82us/step - loss: 1273.7824 - mean_absolute_error: 25.566
32.25840494065058
```

```
In [55]: y_year_pred = model.predict(np.expand_dims(X_year, axis=2))
         print "MEAN Hyderabad" print
         np.mean(y_year),np.mean(y_year_pred) print "Standard
         deviation hyderabad" print
         np.sqrt(np.var(y_year)),np.sqrt(np.var(y_year_pred))
         plot_graphs(y_year,y_year_pred,"Prediction in Hyderabad")
```

```
MEAN Hyderabad
91.48888888888888 100.606964
Standard deviation hyderabad
69.2514651982091 66.957054
```



1.18 Prediction Observations

1.18.1 Training on complete dataset

Algorithm	MAE
Linear Regression	57.08862331011236
SVR	116.60671510825178
Artificial neural nets	44.329664907381066

0

1.18.2 Training on telangana dataset

Algorithm	MAE
Linear Regression	31.249748674622477
SVR	59.35057496896855
Artificial neural nets	31.0601823988415

- Neural Networks performs better than SVR etc.
- Bad performance by SVR model.
- Andhra Pradesh data has a single pattern that can be learned by models, rather than learning different patterns of all states. so has high accuracy.
- Analysed individual year rainfall patterns for Hyderabad district.
- Approximately close means, noticed close standard deviations.

1.19 Conclusions

- Various visualizations of data are observed which helps in implementing the approaches for prediction.
- Prediction of amount of rainfall for both the types of dataset.
- Observations indicates machine learning models won't work well for prediction of rainfall due to fluctutaions in rainfall.

1.20 Technologies

- Programming language : *Python*
- Libraries : *numpy, pandas, matplotlib, seaborn, keras, scipy, sklearn*

Refereces :

https://drive.google.com/drive/folders/1liKt4AGu3_JaB1fkKgQfhPILIOkEuaEW?usp=sharing