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Chapter 1

INTRODUCTION

1 Introduction

Rainfall forecasting is very important because heavy and irregular rainfall can have many impacts like destruction of crops and farms, damage of property so a better forecasting model is essential for an early warning that can minimize risks to life and property and also managing the agricultural farms in better way. This prediction mainly helps farmers and also water resources can be utilized efficiently. Rainfall prediction is a challenging task and the results should be accurate. There are many hardware devices for predicting rainfall by using the weather conditions like temperature, humidity, pressure. These traditional methods cannot work in an efficient way so by using machine learning techniques we can produce accurate results. We can just do it by having the historical data analysis of rainfall and can predict the rainfall for future seasons.

Two types of rainfall predictions can be done; they are - Long term predictions: Predict rainfall over few weeks/months in advance. Short term predictions: 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 can apply many techniques like classification, regression according to the requirements and also we can calculate the error between the actual and prediction and also the accuracy. Different techniques produce different accuracies so it is important to choose the right algorithm and model it according to the requirements.

Regression analysis:

Regression analysis deals with the dependence of one variable (called as dependent variable) on one or more other variables, (called as independent variables) which is useful for estimating and/ or predicting the mean or average value of the former in terms of known or fixed values of the latter. For example, the salary of a person is based on his/her experience here, the experience attribute is independent variable salary is dependent variable. Simple linear regression defines the relationship between a single dependent variable and a single independent variable. The below equation is the general form of regression.

$y = \beta 0 + \beta 1x + \varepsilon$ where $\beta 0$ and $\beta 1$ are parameters, and ε is a probabilistic error term. Regression analysis is a vital tool for modeling and analyzing information. It is used for predictive analysis that is forecasting of rainfall or weather, predicting trends in business, finance, and marketing. It can also be used for correcting errors and also provide quantitative support.

The advantages of regression analysis are:

1. It is a powerful technique for testing relationship between one dependent variable and many independent variables.

2. It allows researchers to control extraneous factors.

3. Regression asses the cumulative effect of multiple factors.

4. It also helps to attain the measure of error using the regression line as a base for estimations.

Chapter 2

SOFTWARE & HARDWARE REQUIREMENTS

2 Software & Hardware Requirement

2.1 Software Requirement

2.1.1 Anaconda

2.1.2 Jupyter NoteBook

2.1.3 Python

2.1.4 Python Libraries

2.1.4.1 Pandas

2.1.4.2 Seaborn

2.1.4.3 Keras

2.1.4.4 SciPy

2.1.4.5 SkLearn

2.1.4.6 NumPy

2.2 Hardware Requirement

2.2.1 Windows 10 – 64 Bit

2.2.2 AMD Ryzen 5 Gen 3rd

2.2.3 RAM 8 GB

Chapter 3

LITERATURE SURVEY

3. Literature Survey

Thirumalai, Chandrasegar, et al. [1] discusses the amount of rainfall in past years according to the crop seasons and predicts the rainfall for future years. The crop seasons are Rabi, Kharif and Zaid. Linear regression method is applied for early prediction. Here, Rabi and kharif were taken as variables if one variable was given then other can be predicted using linear regression. Standard deviation and Mean was also calculated for future prediction of crop seasons. This implementation will be used for farmers to have an idea of which crop to harvest according to crop seasons. Geetha, A., and G. M. Nasira. [2] implements a model which predicts the weather conditions like rainfall, fog, thunderstorms and cyclones which will be helpful to the people to take preventive measures.

Data mining techniques were used and a data mining tool named Rapid miner was used to model the decision trees. The data set of Trivandrum with attributes like day, temperature, dew point, pressure etc. The dataset is divided into training set and testing set and decision tree algorithm is applied. The accuracy is calculated, actual and predicted values are compared. The accuracy is 80.67 and to achieve high value it can be extended by applying soft computing techniques like fuzzy logic and genetic algorithms. Parmar, Aakash, Kinjal Mistree, and Mithila Sompura [3] discusses the different methods used for rainfall prediction for weather forecasting with their limitations. Various neural networks algorithm which are used for prediction are discussed with their steps in detail categorizes various approaches and algorithms used for rainfall prediction by various researchers in today's era. Finally, presents conclusion of paper. Done the background work about some models of machine learning ARIMA Model, Artificial neural network and types like Back- Propagation Neural Network - Cascade Forward Back Propagation Network Layer Recurrent Network, Self-Organizing Map and Support Vector Machine, Collected, surveyed and table presents categorization of different approaches of rainfall prediction.

Dash, Yajnaseni, Saroj K. Mishra, and Bijaya K. Panigrahi [4] has used artificial intelligence techniques like Artificial Neural Network (ANN), Extreme Learning Machine (ELM), K nearest neighbor (KNN) are applied for prediction of summer monsoon and post monsoon rainfall. The dataset used is the time series data of Kerala from 1871 to 2016 taken from Indian Institute of Tropical Meteorology (IITM).The data is pre-processed and normalization was performed on the data next, the data is divided into training and testing the data up to 2010 was taken as training set and the data from 2011- 2016 taken as test set. The above mentioned algorithms were applied and its performance was calculated by using MAE, RMSE, and MASE. The ELM algorithm has given accurate results compared to the others. Singh, Gurpreet, and Deepak Kumar[5] states that there are many machine learning algorithms applied for the prediction of rainfall and in this, they have used a hybrid approach that is combining two techniques, Random forest and Gradient boosting with many machine learning techniques like ada boost, K-Nearest Neighbor(KNN), Support vector machine(SVM), and Neural Network(NN).These have been applied on the rainfall data of North Carolina from 2007 – 2017 and also the performance is calculated by applying different metrics F-score, precision, accuracy, recall.

Finally, eight hybrid models have been proposed and Gradient boosting-Ada boost has been the superior which exhibited good results. Kar, Kaveri, Neelima Thakur, and Prerika Sanghvi [6] has used the fuzzy logic approach for the prediction of rainfall on the data of temperature in a geographic location. The fuzzy model has been applied Due to other climatic factors the prediction is not accurate so they have considered other influencing factors like humidity also analyzed the advantages of fuzzy system over other techniques. Sardeshpande, Kaushik D., and Vijaya R. Thool [7] has used the artificial neural networks, back propagation (BPNN), radial basis function (RBFNN) and generalized regression (GRNN) on the rainfall data of India mainly Nanded district, Maharashtra was considered and the data is normalized between 0 to 1 and the algorithms are applied and the performance of those was calculated and compared. BPNN and RBFNN has given good results

compared to GRNN. Chen, Binghong, et al. [8] focuses on the non-linear machine learning approaches like gradient boosting decision tree model and deep neural networks for a short term prediction of rainfall and these algorithms were built on Alibaba cloud and data was collected from different sites and effectiveness is calculated by using classification metrics AUC, F1 score, precision and accuracy and by Regression metric RMSE, correlation. It has been observed that DNN showed better result than ECData. Moon, Seung-Hyun, et al [9] implements an early warning system (EWS) that produces a signal when it reaches a threshold limit that givesWarning before 3 hrs. This was done by using machine learning techniques. South Korea data from 2007 to 2012 was taken and performance is measured by some criteria and a confusion matrix was produced. The logistic regression with feature selection and PCA was proposed. F-measure is calculated for estimating the efficiency of model.

Chapter 4

SOFTWARE REQUIREMENT ANALYSIS

4 Software Requirement Analysis

4.1 Problem Statement

Rainfall prediction remains a serious concern and has attracted the attention of governments, industries, risk management entities, as well as the scientific community. Rainfall is a climatic factor that affects many human activities like agricultural production, construction, power generation, forestry and tourism, among others. As we know heavy and irregular rainfall can have many impacts like destruction of crops and farms, damage of property so a better forecasting model is essential for an early warning that can minimize risks to life and property and also managing the agricultural farms in better way. Therefore, having an appropriate approach for rainfall prediction is also required to counter these problems. This project is made focussing these problems.

4.2 Proposed Method for Solution

The predictive model is used to prediction of the precipitation. The first step is converting data in to the correct format to conduct experiments then make a good analysis of data and observe variation in the patterns of rainfall. We predict the rainfall by separating the dataset into training set and testing set then we apply different machine learning approaches (MLR, SVR, etc.) and statistical techniques and compare and draw analysis over various approaches used. With the help of numerous approaches we attempt to minimize the error.

Dataset Description:
The dataset [10] consists of the measurement of rainfall from year 1901-2015 for each state.
• Data consists of 19 attributes (individual months, annual, and combinations of 3 consecutive months) for 36 sub divisions.
• The data is available only from 1950 to 2015 for some of the subdivisions
• The attributes are the amount of rainfall measured in mm

As the dataset is very large, feature reduction is done so that it improves the accuracy, reduces the computation time and also storage. Principal Component Analysis (PCA) is a technique of extracting necessary variables from a huge set of variables. It extracts low dimensional set with a motive to capture the maximum amount of information. With few variables, visualization becomes more significant. It is done by using covariance matrix and by obtaining Eigen values from it. In our dataset by using PCA it has reduced the attributes by considering only the rainfall data of combination of three consecutive months and annual data from every subdivision. Techniques used: Multiple Linear Regression: Multiple regression tries to model the connection between two or additional variables and a response by fitting an equation to determined information. Clearly, it's nothing however an extension of straight forward regression toward the mean. The general form of multivariable linear regression model is: $y=\alpha+\beta 1x1+ \beta 2x2+\ldots+ \beta kxk+\varepsilon$ where y = dependent variable and x1, x2… xk are independent variables,α,β are coefficients. Multiple regression will model additional complicated relationship that comes from numerous options along they should to be employed in cases wherever one explicit variable isn't evident enough to map the link between the independent and also the variable quantity.

Support Vector Regression:
Support Vector regression machine learning and data science with the term SVM or support vector machine but SVR that is support vector regression is a bit different from SVM that is support vector machine as the name suggests that is integration algorithm so we can use SVR for working with continuous value instead of classification which is SVM Support Vector Machines support linear and nonlinear regression that we can refer

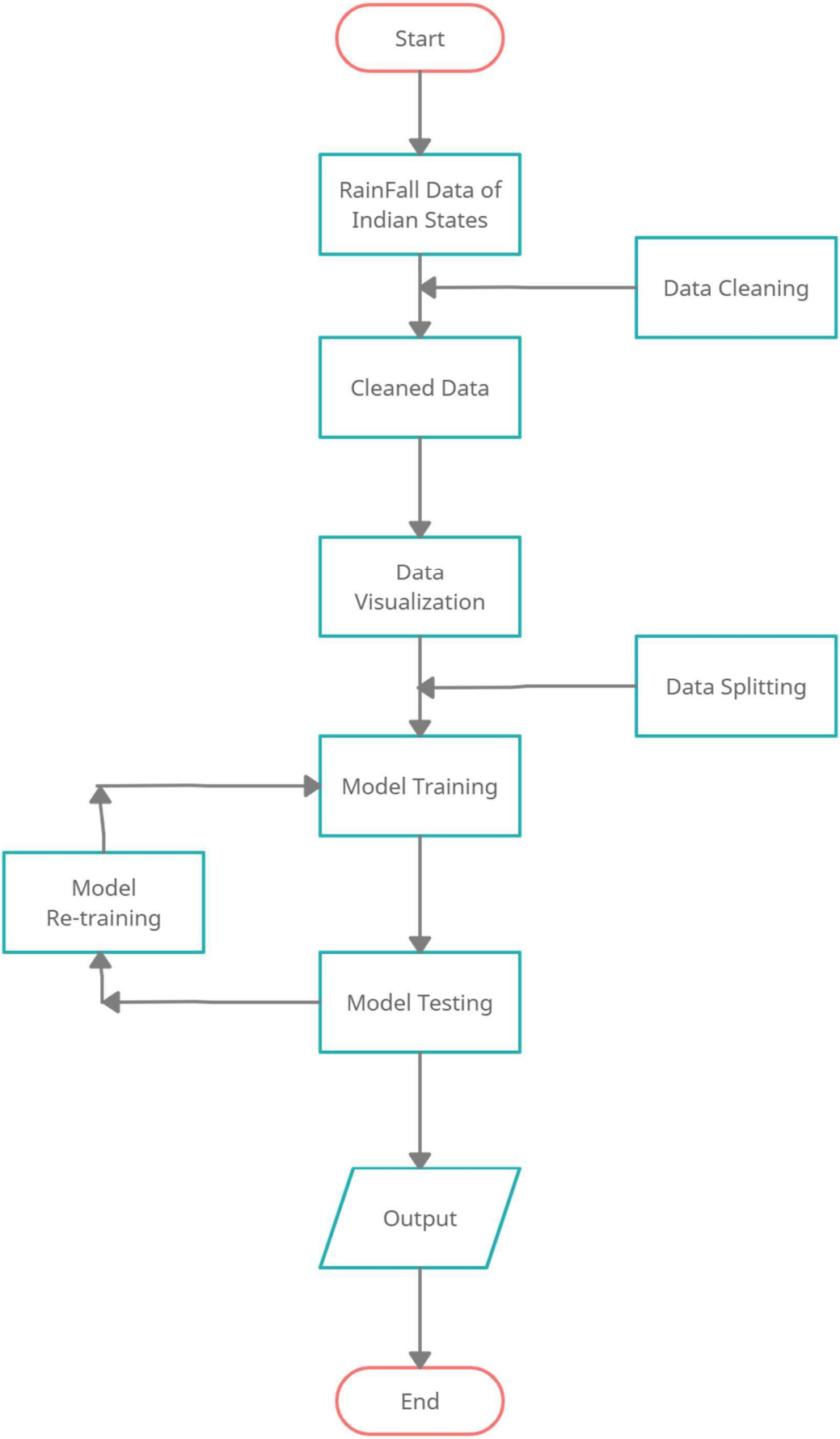
to as Support Vector Regression. Instead of trying to fit the largest possible street between two classes while limiting margin violations, Support Vector Regression tries to fit as many instances as possible on the street while limiting margin violations. The size of the lane is measured by a hyper parameter Epsilon.

Kernel- The function used to map a low dimensional data into higher dimensional data.
Hyper plane- in SVM this is a basically The Separation line between the data classes also in SVR we are going to define it is as the line that will that will help us to predict the continuous value or target value. Boundary line - the SVM plane which creates imagine the support vector can be on boundary lines or outside the boundary line separates two classes in the concept same. Vectors-these are the data points which are closest to the boundary the distance of the point is minimum. SVR performs linear regression in higher dimensional space. We can think of SVR as if each data point in the training represents its own dimension. When we evaluate kernel between a test point and a point in the training set the resulting value gives you the coordinate of your test point in that dimension. The vector we get when we evaluate the test point for all points in the training set, k is the representation of the test point in the higher dimensional space. The equation of the hyper plane is wx+b=0 and the two equations of boundary lines is Wx+b=+e, Wx+b=-e Equation that satisfy our SVR is e<=y-Wx-b<=+e SVR has a different regression goal compared to linear regression in linear regression, we are trying to minimize the error between the prediction and data whereas in SVR a goal is to make sure that error do not exceed the threshold.

Chapter 5

SOFTWARE DESIGN

5.1 Data Flow Diagram



Chapter 6

CODE TEMPLATES AND RESULTS

6 Code Templates and Outputs

1.1 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.

1.2 Methodology

- Converting data into 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
```

1.3 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
```

1.4 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	Jun-Sep	Oct-Dec
0	365.1	481.1	332.6	388.5	558.2	33.6	3373.2	136.3	560.3	1696.3	980.3
1	228.9	753.7	666.2	197.2	359.0	160.5	3520.7	159.8	458.3	2185.9	716.7
2	728.4	326.7	339.0	181.2	284.4	225.0	2957.4	156.7	236.1	1874.0	690.6
3	502.0	160.1	820.4	222.2	308.7	40.1	3079.6	24.1	506.9	1977.6	571.0
4	368.7	330.5	297.0	260.7	25.4	344.7	2566.7	1.3	309.7	1624.9	630.8

In[4]: data.describle()

Out[4]:

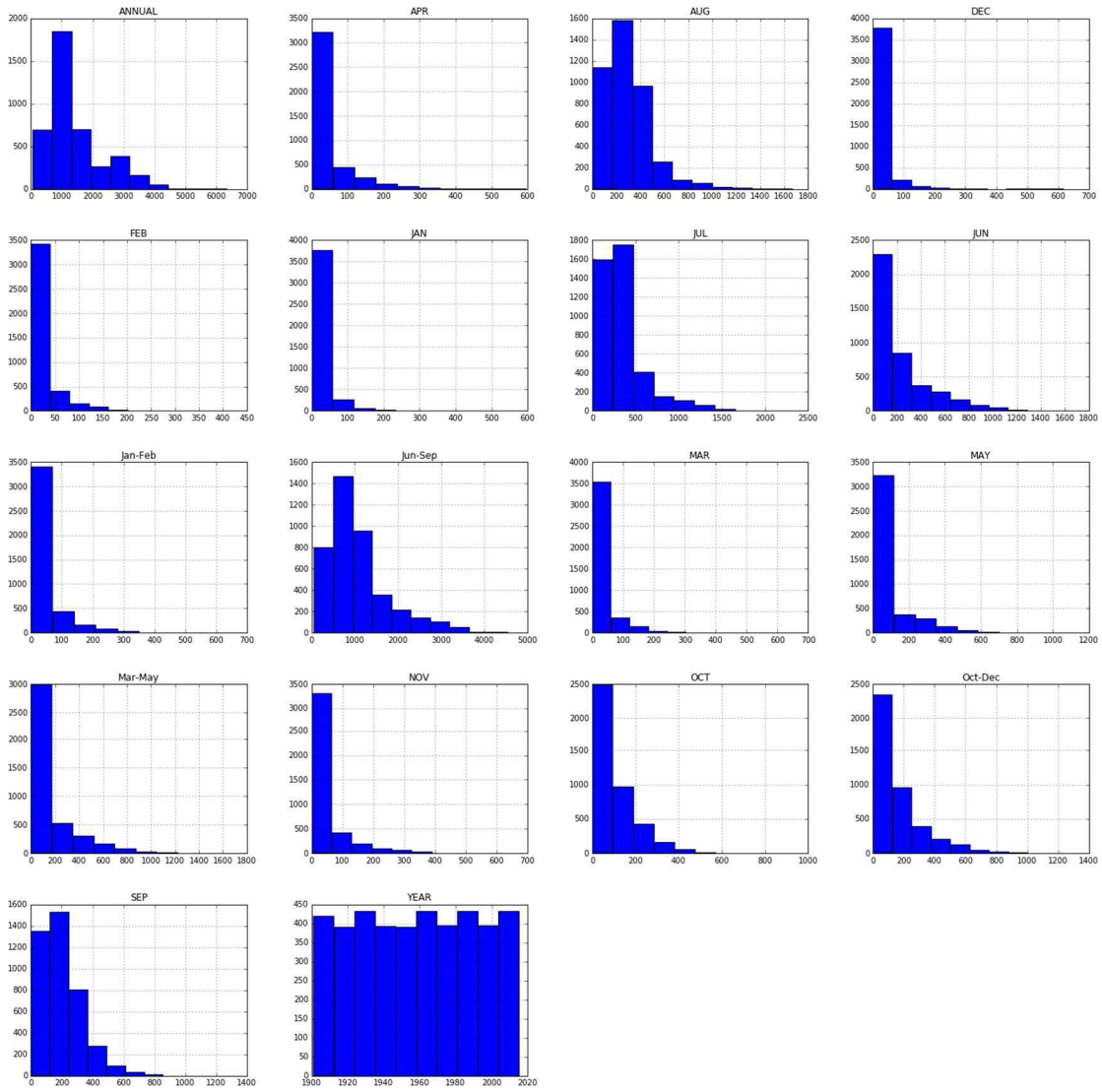
	YEAR	JAN	FEB	MAR	APR	\
count	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	
mean	1958.218659	18.957320	21.805325	27.359197	43.127432	
std	33.140898	33.569044	35.896396	46.925176	67.798192	
% min	1901.000000	0.000000	0.000000	0.000000	0.000000	
%						
% 25□	1930.000000	0.600000	0.600000	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	
%	0	0	0	0		
%						

	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

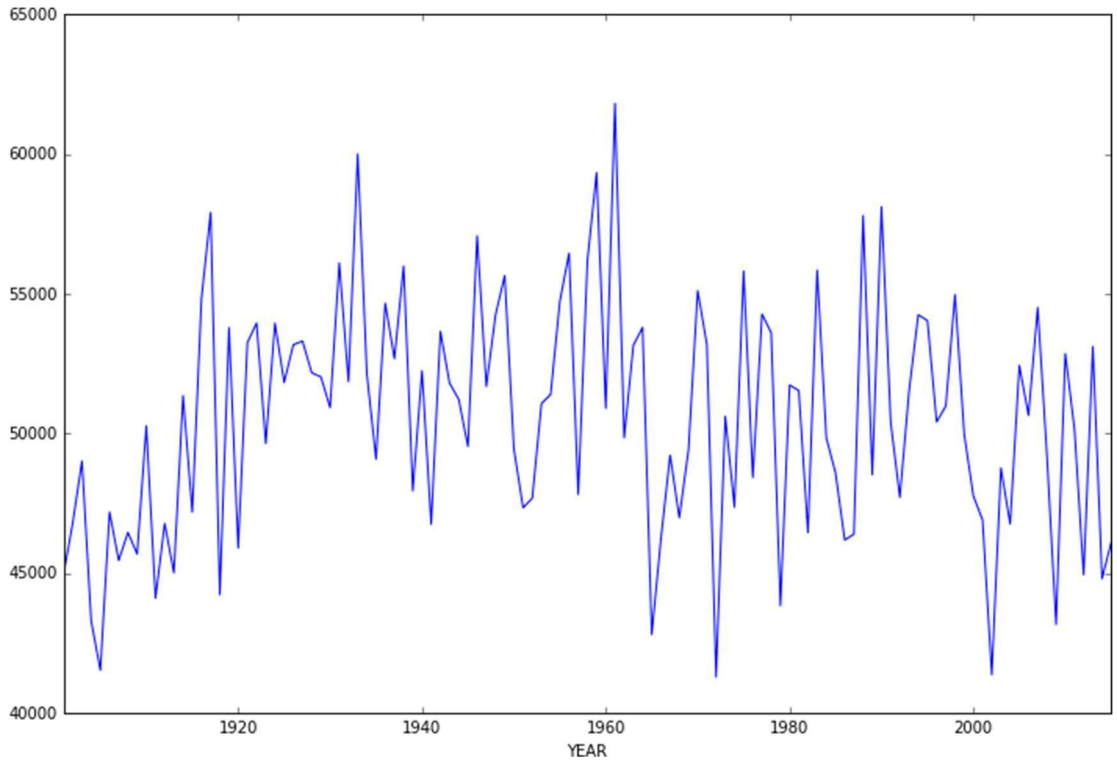
In [5]: data.hist(figsize=(24,24));



1.5 Observations

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

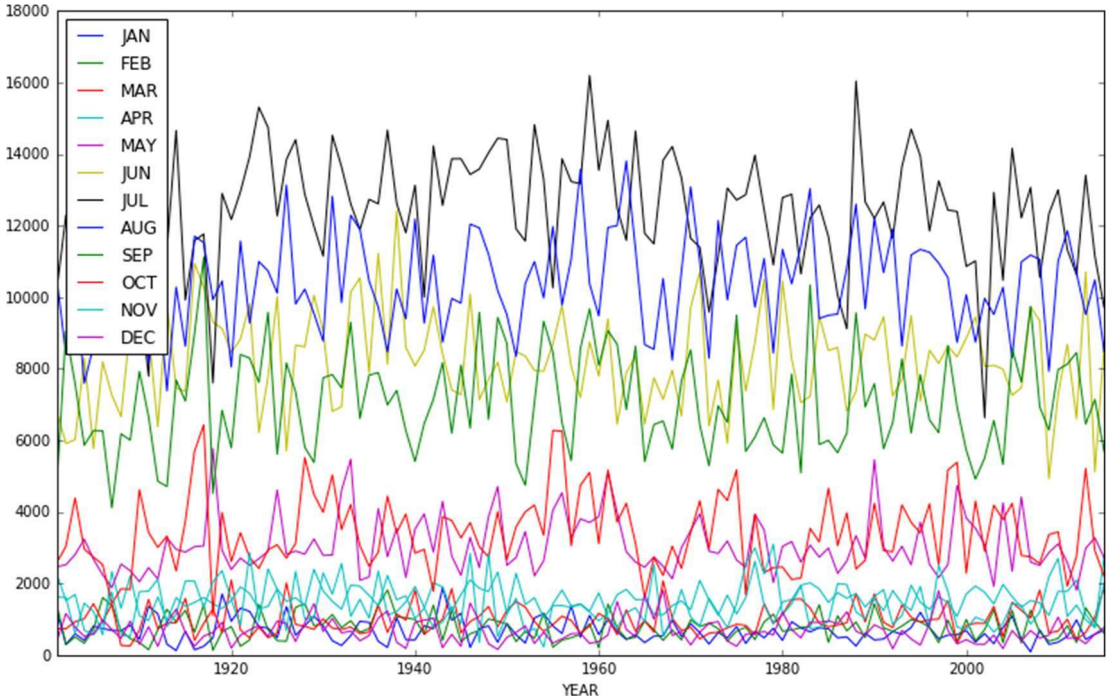
In [6]: data.groupby("YEAR").sum()['ANNUAL'].plot(figsize=(12,8));



1.6 Observations

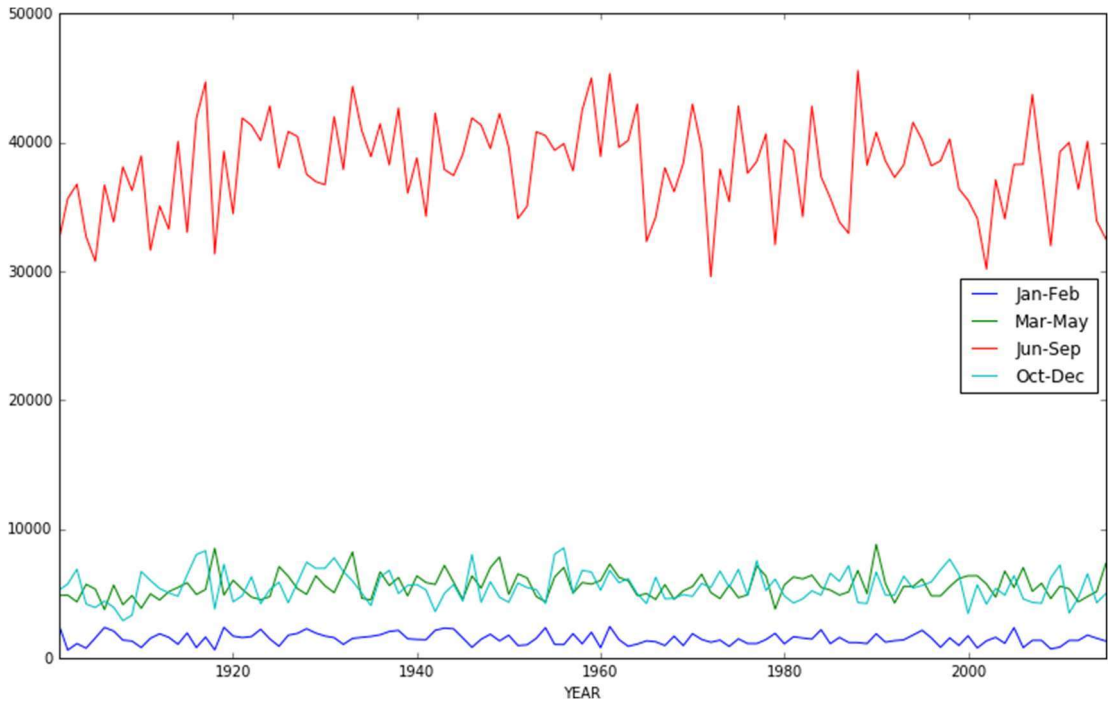
- Shows distribution of rainfall over years.
- Observed high amount of rainfall in 1950s.

```
In [7]: data[['YEAR', 'JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
                'AUG', 'SEP', 'OCT', 'NOV', 'DEC']]
```




```
C']].groupby("YEAR").sum().plot(figsize=(13,8));
```

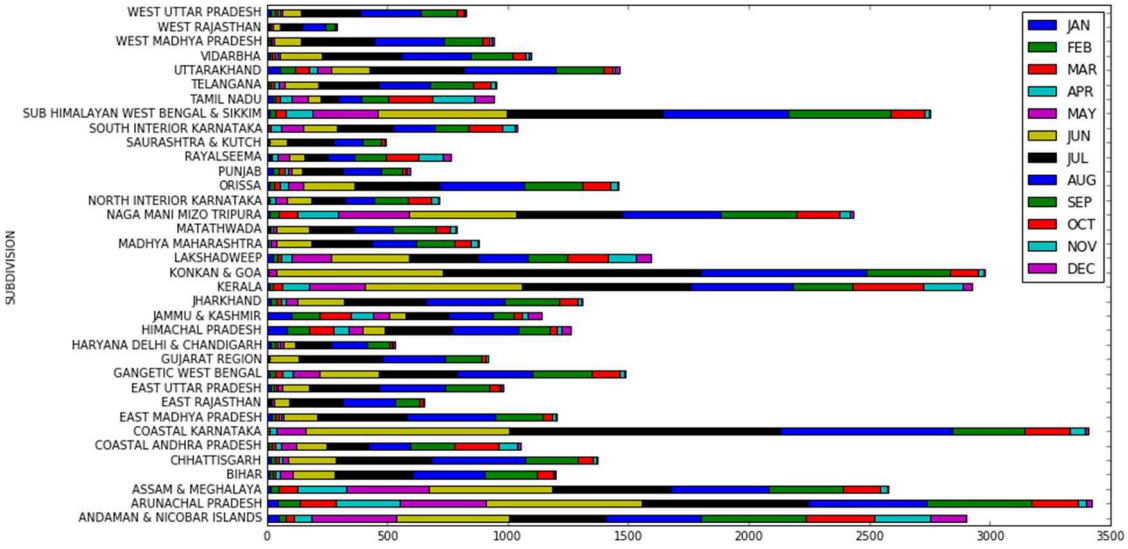
```
In [8]: data[['YEAR','Jan-Feb', 'Mar-May',
              'Jun-Sep', 'Oct-Dec']].groupby("YEAR").sum().plot(figsize=(13,8));
```



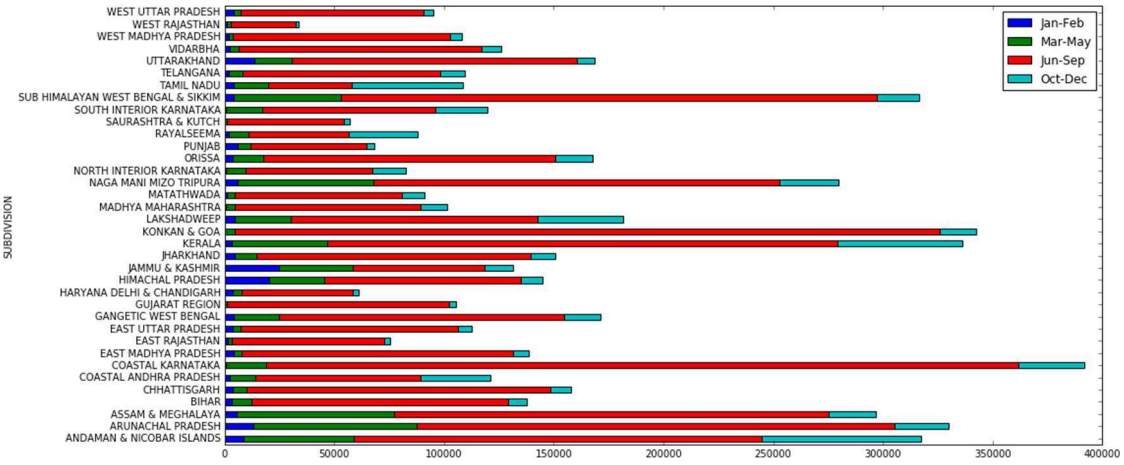
1.7 Observations

- 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,
```

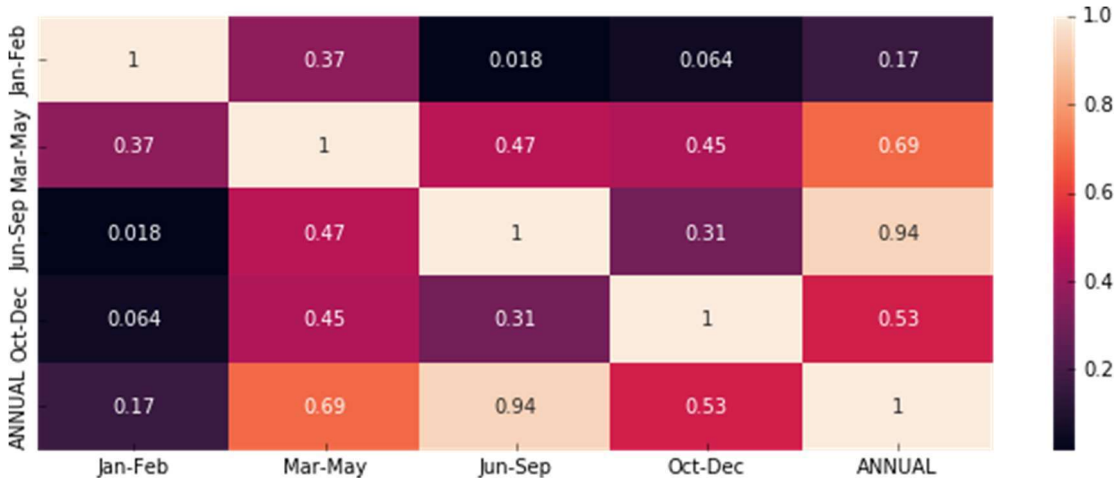


1.8 Observations

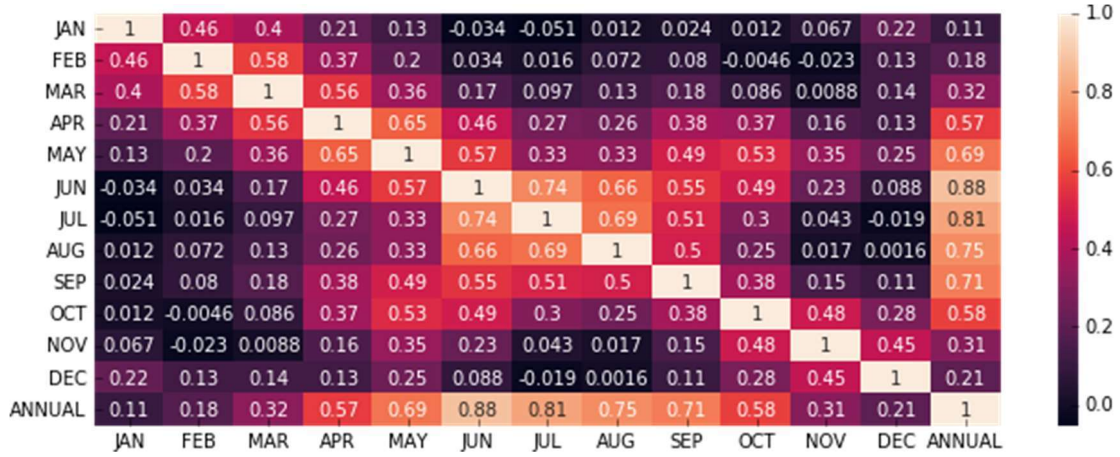
- Above two graphs shows that the amount of rainfall is reasonably good in the months of march, april, may in eastern India.

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

```
/home/sudheer.achary/.local/lib/python2.7/site-packages/pandas/core/computation/check.py:17: UserWarnin
The minimum supported version is 2.4.6

  ver=ver, min_ver=_MIN_NUMEXPR_VERSION), UserWarning)
```



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



1.9 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()
```

1.10 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)
```

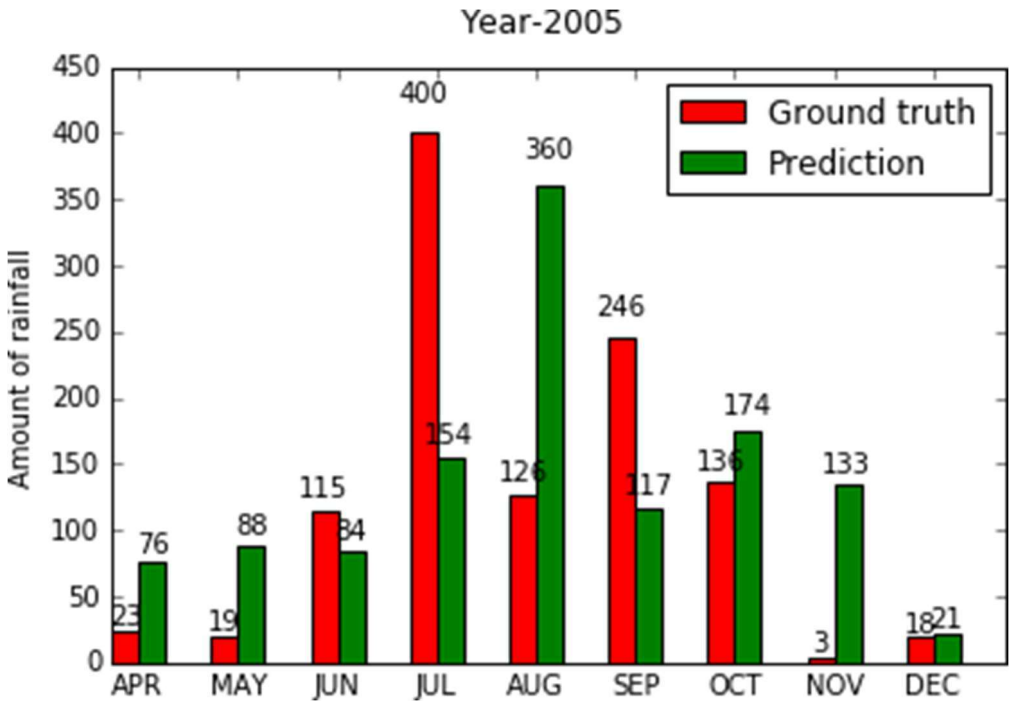
In [18]:
```
from sklearn import linear_model

    # 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)
```

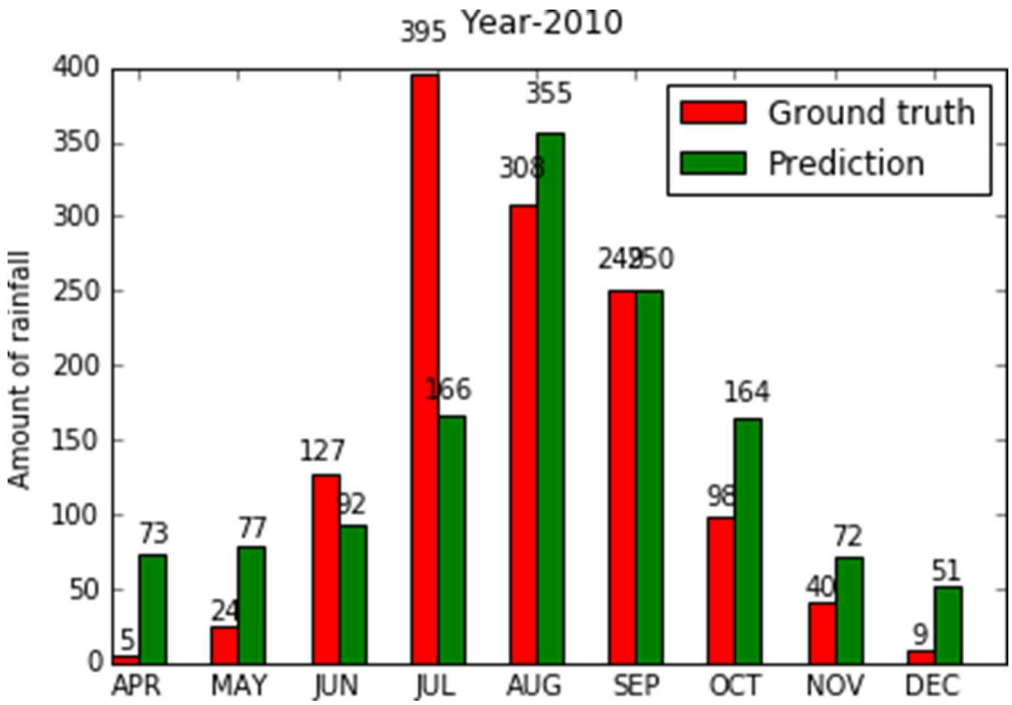
```
96.32435229744095
```

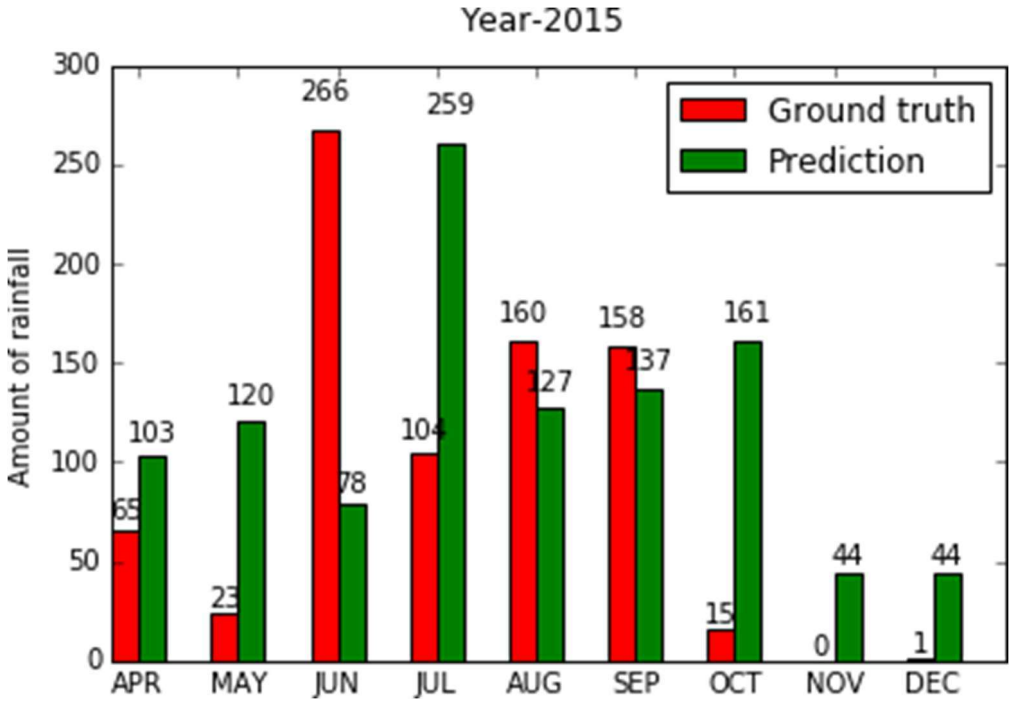
In [19]:
```
#2005
    y_year_pred_2005 = reg.predict(X_year_2005)


    #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
```


Year-2005
Amount of rainfall
Ground truth
Prediction
450
400
350
300
250
200
150
100
50
0
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
23
76
19
88
115
84
400
154
126
360
246
117
136
174
3
133
18
21





In [20]: from sklearn.svm import SVR

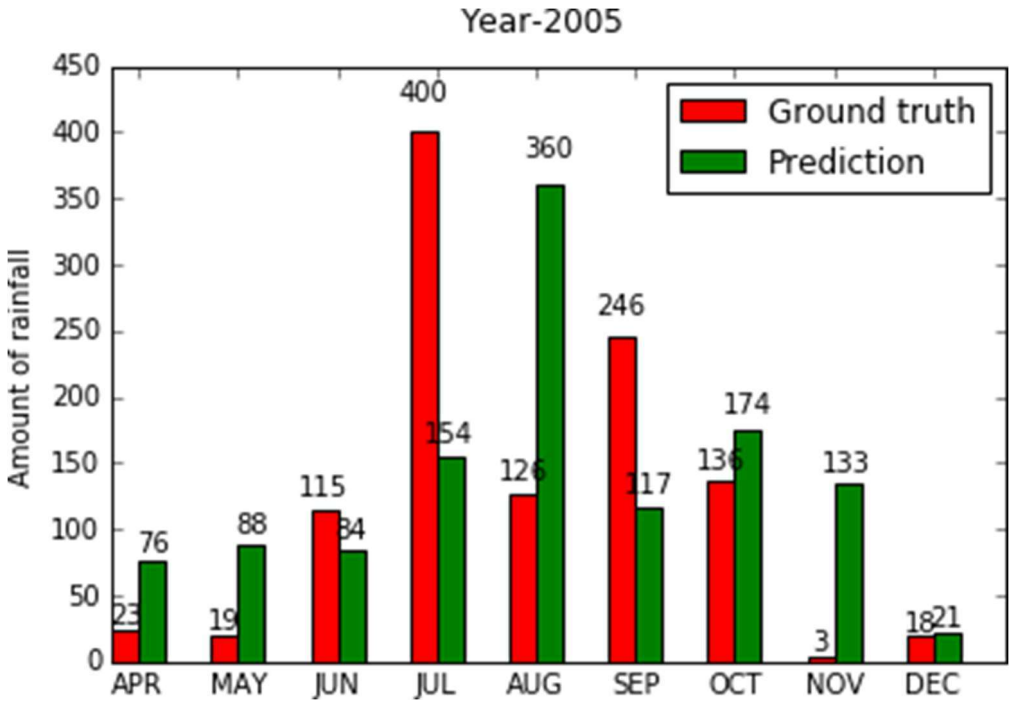
```
        # SVM model
        clf = SVR(gamma='auto', C=0.1, epsilon=0.2)
        clf.fit(X_train, y_train)
        y_pred = clf.predict(X_test)
        print mean_absolute_error(y_test, y_pred)
```

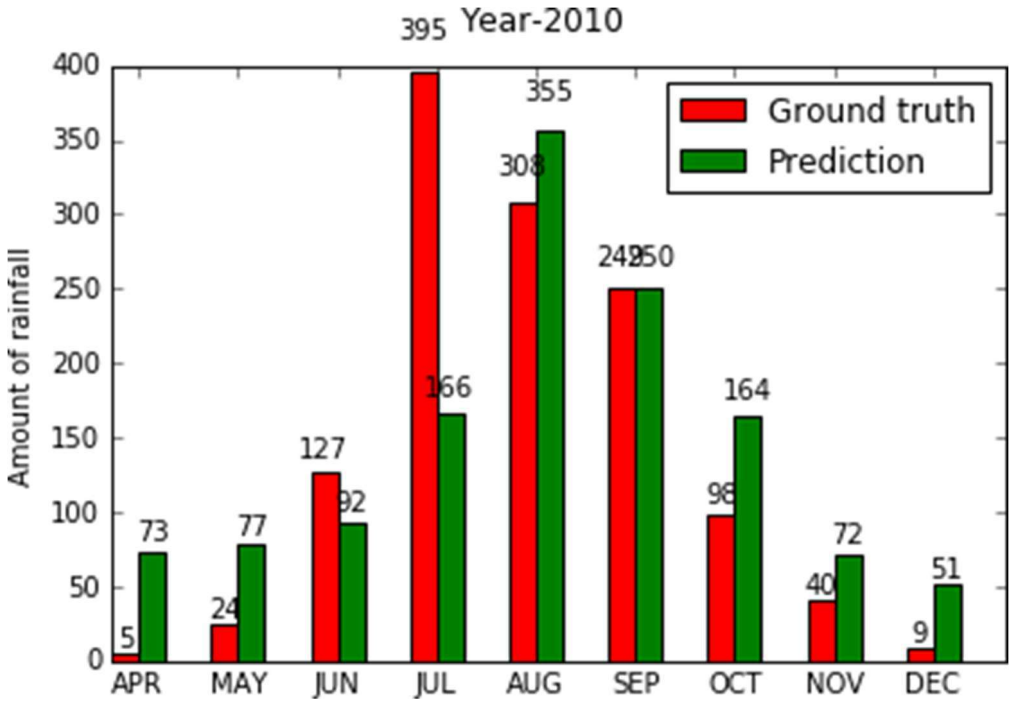
127.1600615632603

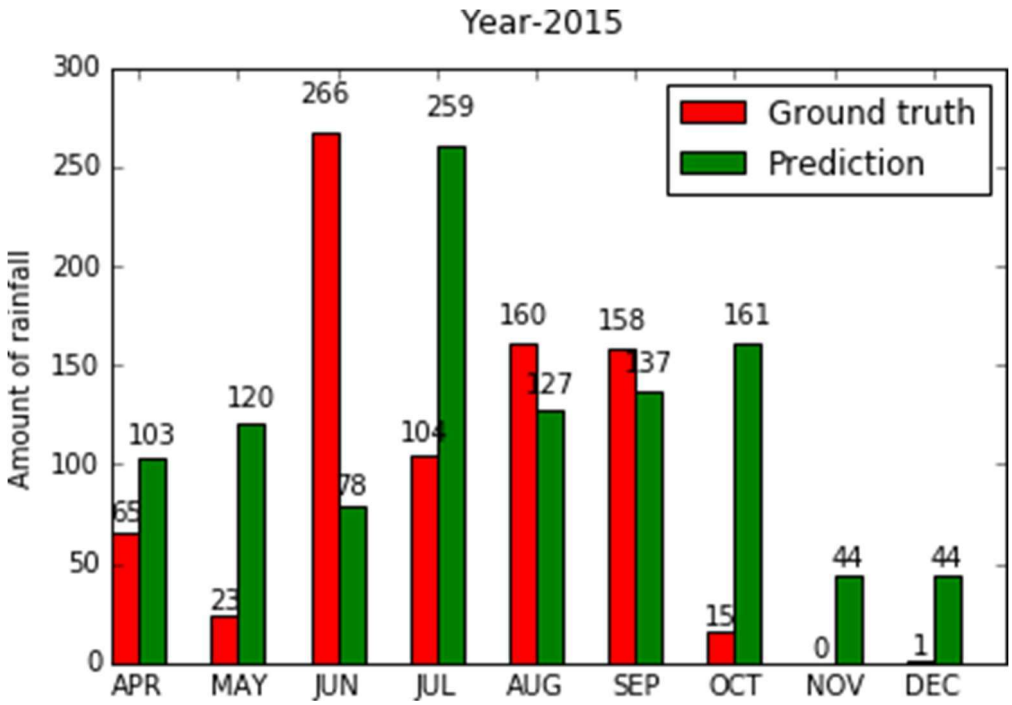
```
In [21]: #2005
        y_year_pred_2005 = reg.predict(X_year_2005)

        #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


Year-2005
Amount of rainfall
Ground truth
Prediction
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC


Year-2010
Amount of rainfall
Ground truth
Prediction
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC



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)
```

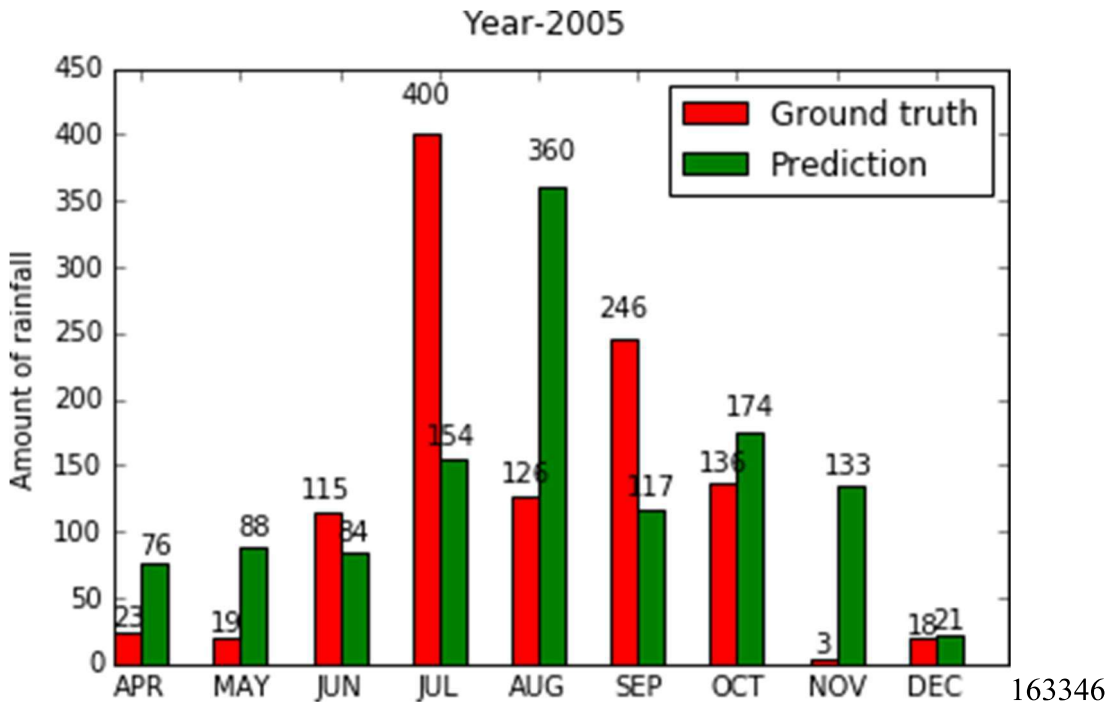
Train on 30005 samples, validate on 3334 samples

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))
```

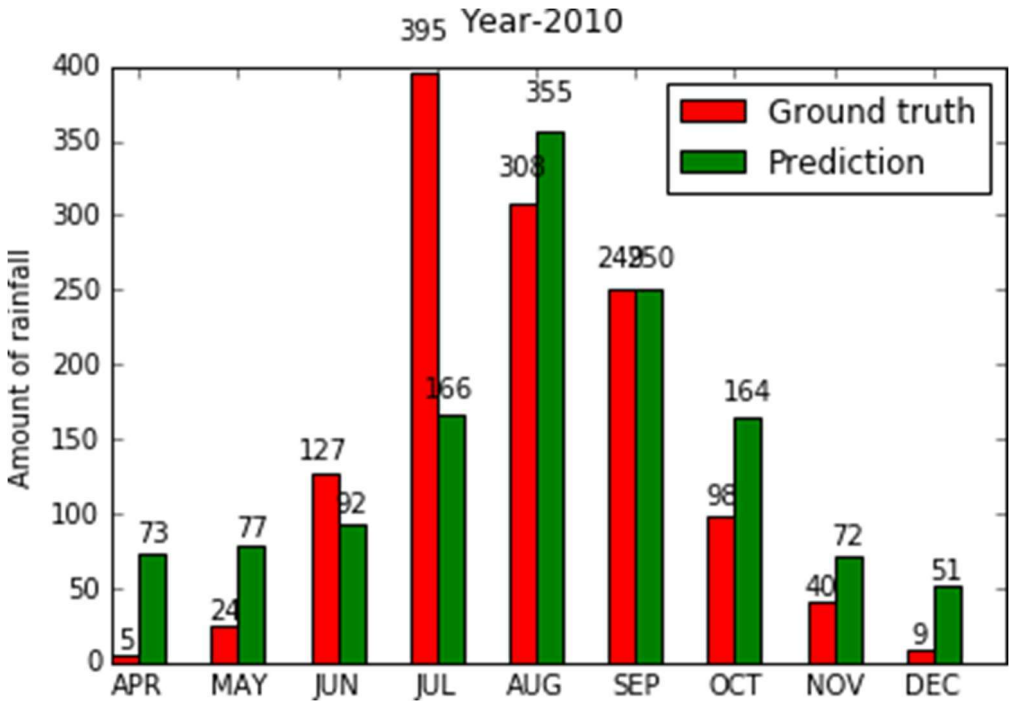
```
print "MEAN 2015"
print
np.mean(y_year_2015),np.mean(y_year_pred_2015)
print "Standard deviation 2015"
print  np.sqrt(np.var(y_year_2015)),np.sqrt(np.var(y_year_pred_2015))

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")
```

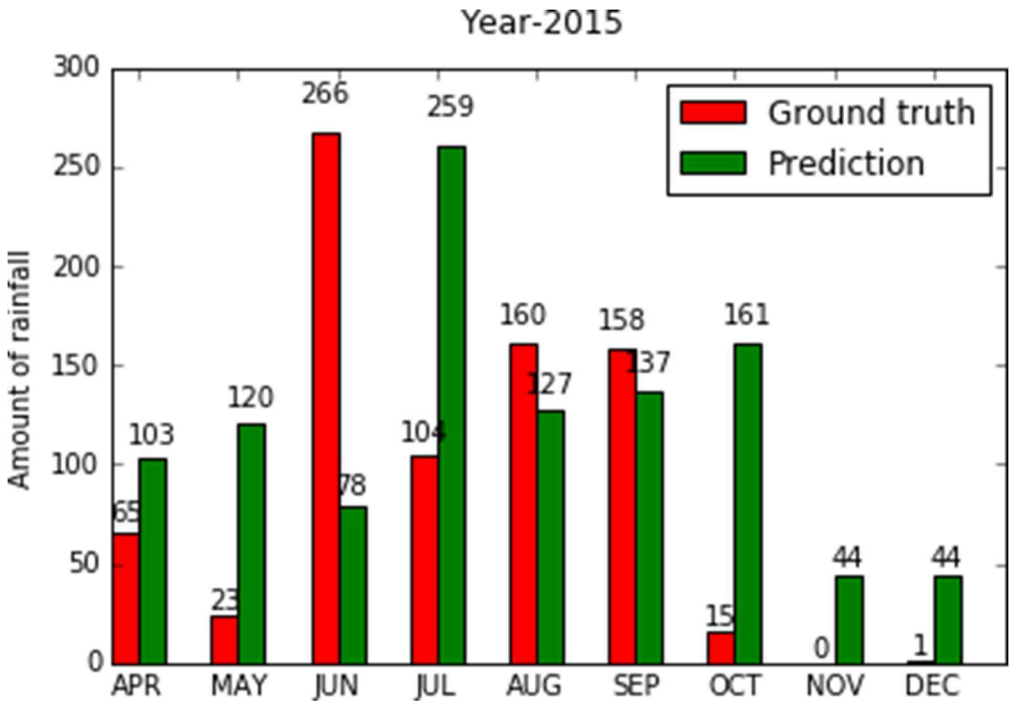
```
MEAN 2005
121.2111111111111 134.68699821349824
Standard deviation 2005
123.77066107608005 90.86310230416397
MEAN 2010
139.93333333333334 144.8050132651592
Standard deviation 2010
135.71320250194282 95.94931363601675
MEAN 2015
88.52222222222223 119.64752006738864
Standard deviation 2015
86.62446123324875 62.36355370
```



163346

```
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: 
```


395 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
73
24
77
127
92
166
395
308
355
242
250
98
164
40
72
9
51



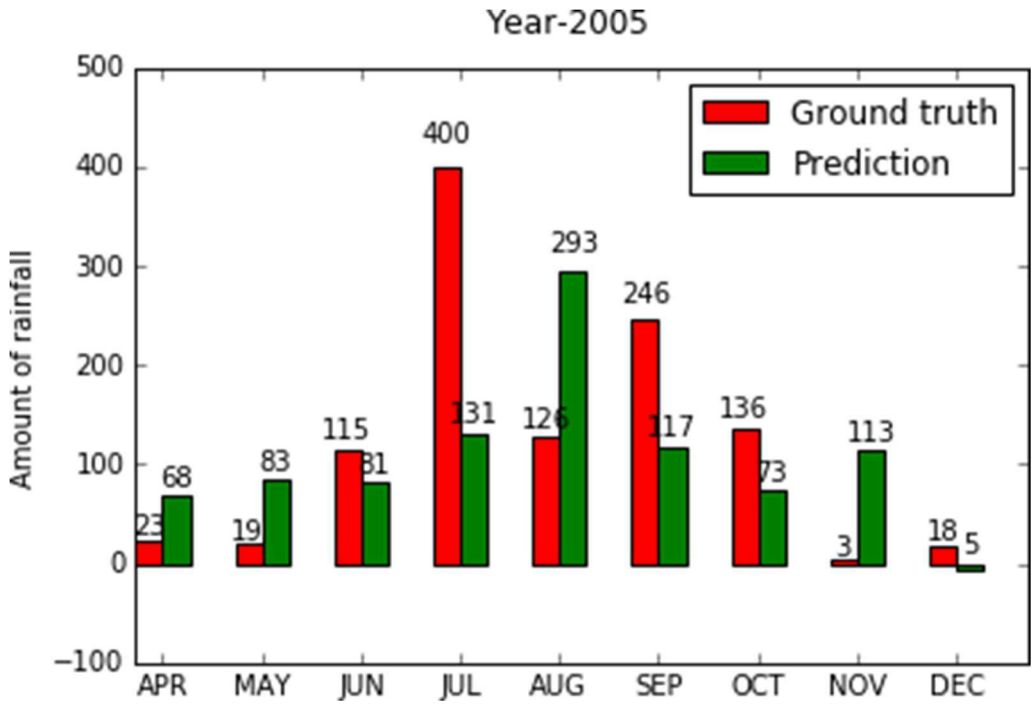
In [25]:
```
# spliting training and testing data only for telangana
telangana = np.asarray(data[['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
        'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].loc[data['SUBDIVISION'] == 'TELANGANA'])

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)
```

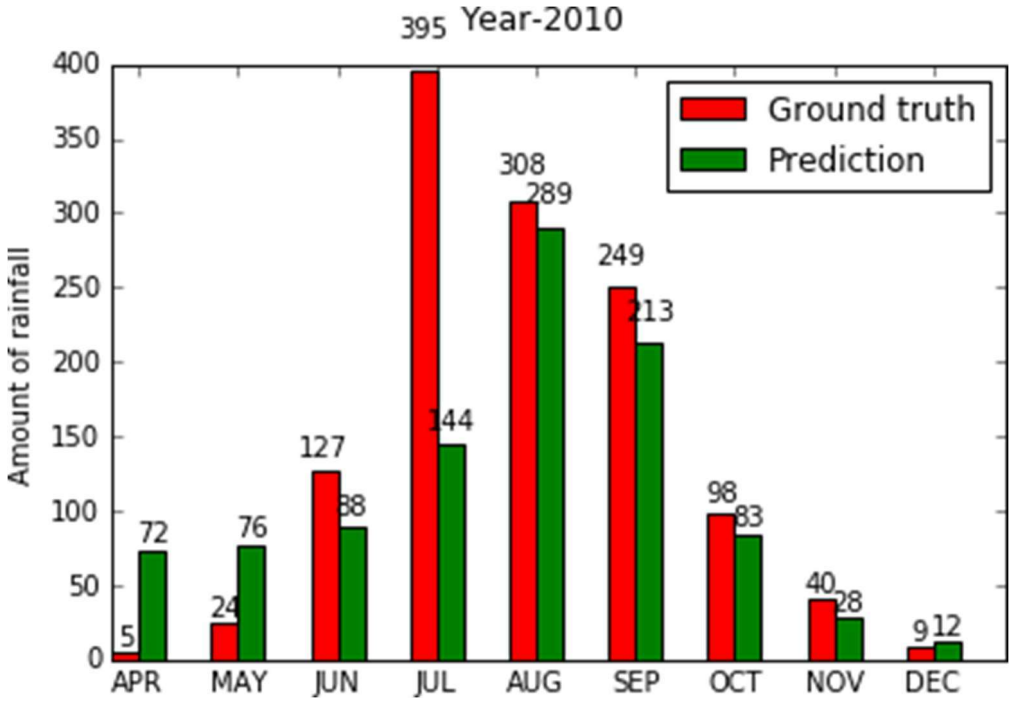
In [26]:
```
from sklearn import linear_model

# 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)
```

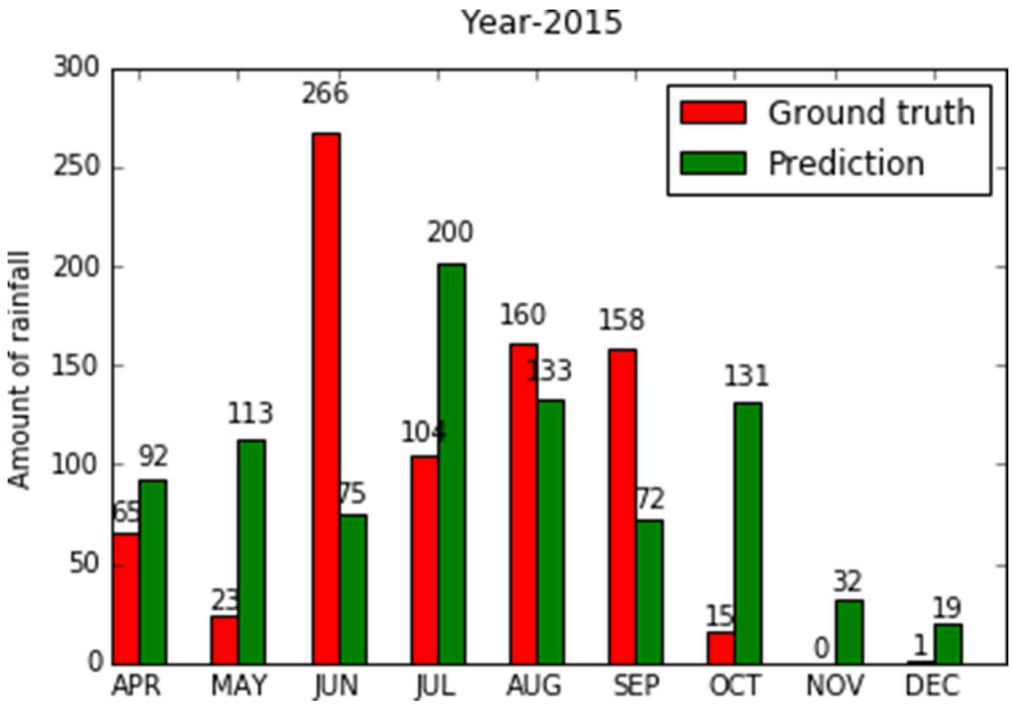
64.72601914484643

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
```


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


395 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
144
308
289
249
213
98
83
40
28
9
12



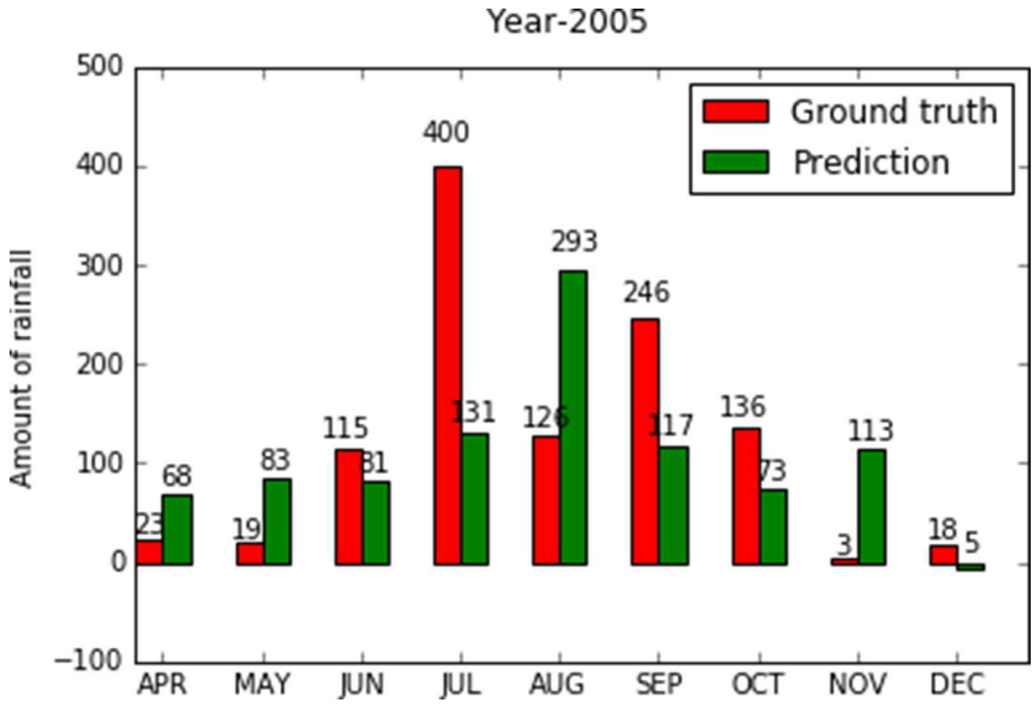
In [28]:
```
from sklearn.svm import SVR

# 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)
```

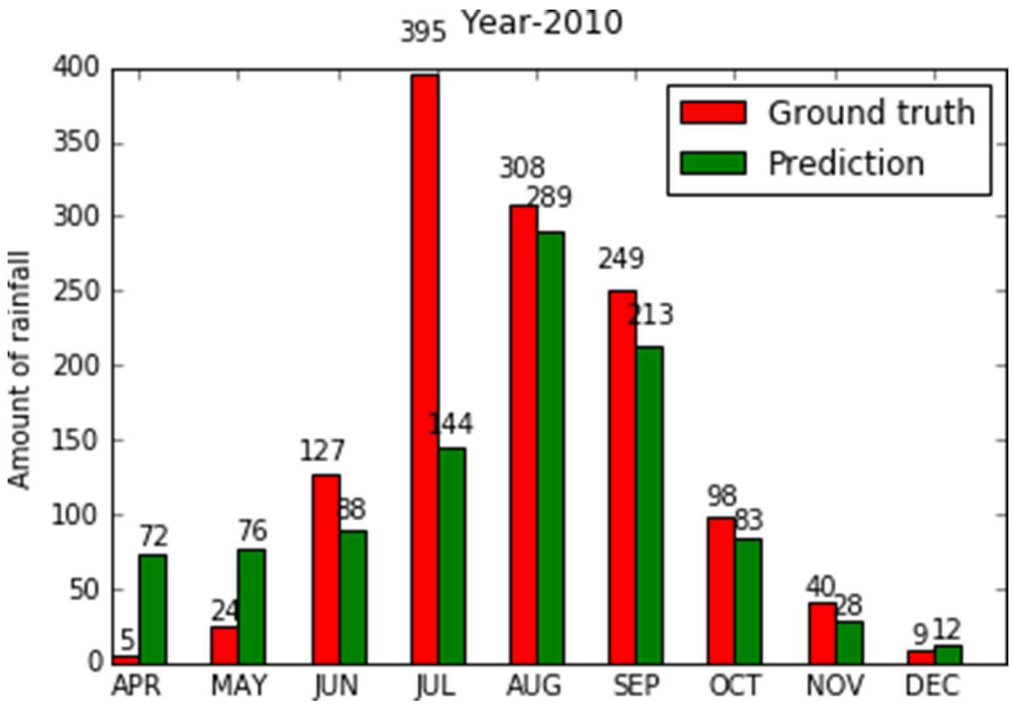
115.32415990638656

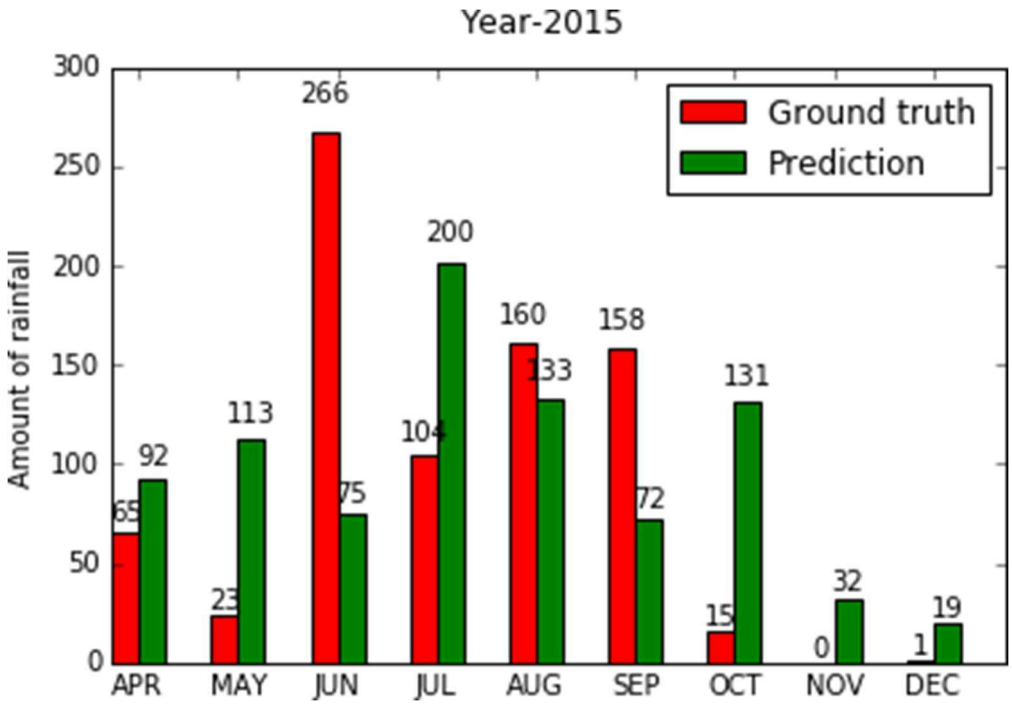
In [29]:
```
#2005
y_year_pred_2005 = reg.predict(X_year_2005)

#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
```







In [30]: model.fit(x=np.expand_dims(X_train, axis=2), y=y_train, batch_size=64, epochs=10, verbose=1, v

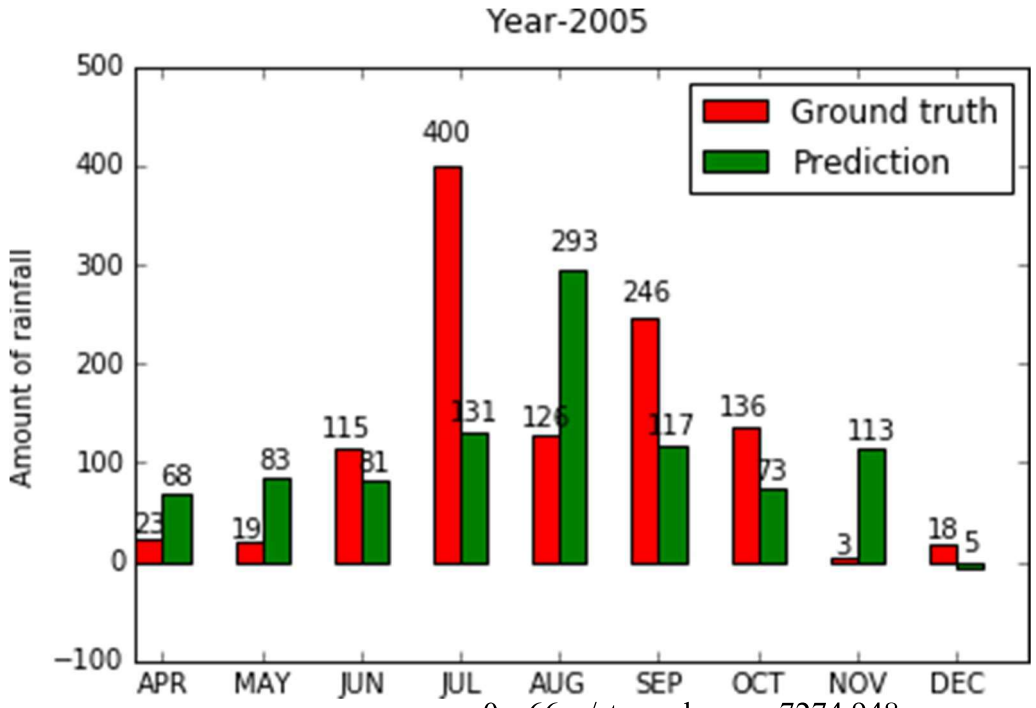
```
        y_pred = model.predict(np.expand_dims(X_test,
        axis=2)) print mean_absolute_error(y_test, y_pred)
```

```
Train on 921 samples, validate on 103 samples
Epoch 1/10
```

In [31]:
```
        #2005
        y_year_pred_200 = reg.predict(X_year_2005)
        5

        #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
```

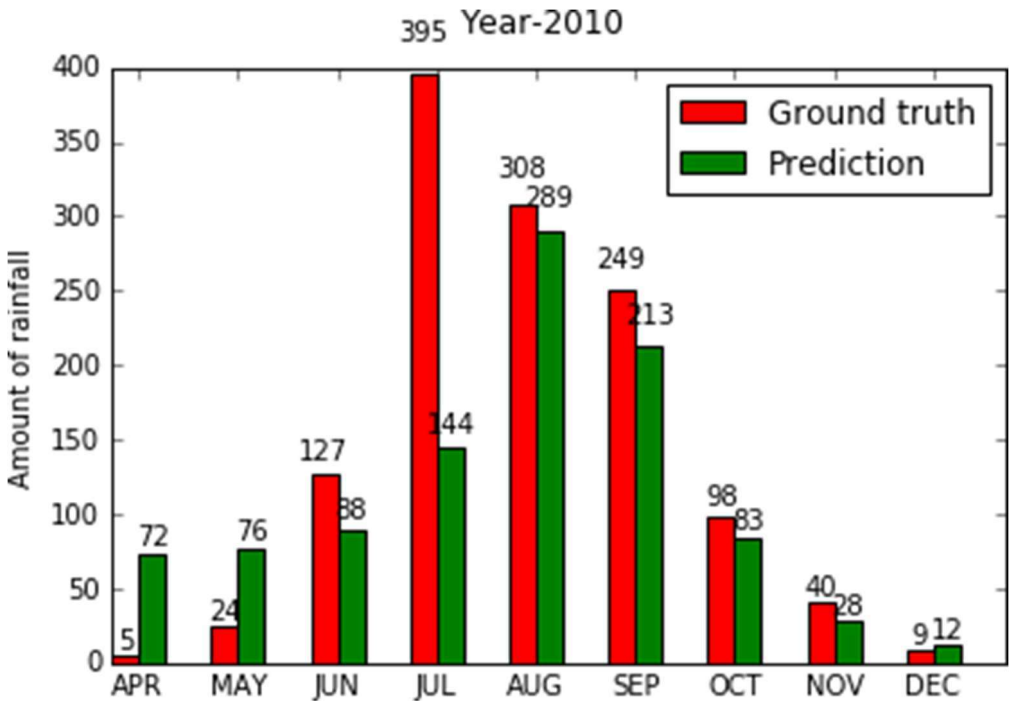
```
plot_graphs(y_year_2015,y_year_pred_2015,"Year-2015")
```

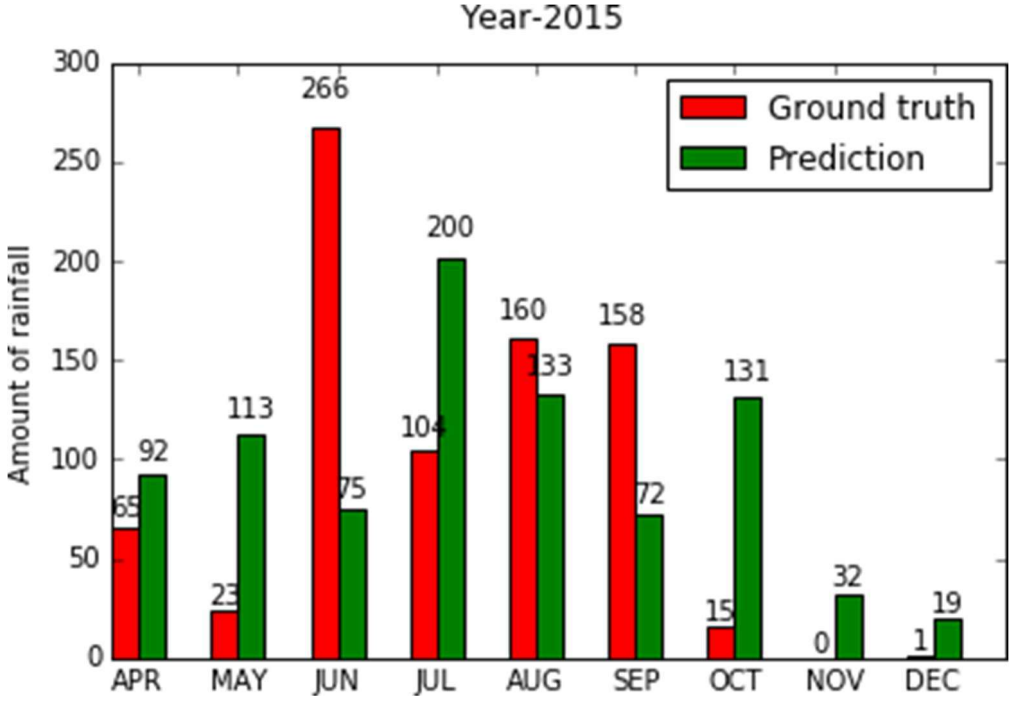
```
MEAN 2005
121.2111111111111 106.49798150231584
Standard deviation 2005
123.77066107608005 76.08558540019227
MEAN 2010
139.93333333333334 112.18662987131034
Standard deviation 2010
135.71320250194282 84.35813629737324
MEAN 2015
88.52222222222223 96.76817006572782
Standard deviation 2015
86.62446123324875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




```
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
```


395 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
144
308
289
249
213
98
83
40
28
9
12


Year-2015
Ground truth
Prediction
Amount of rainfall
300
250
200
150
100
50
0
APR
MAY
JUN
JUL
AUG
SEP
OCT
NOV
DEC
65
92
23
113
266
75
104
200
160
133
158
72
15
131
0
32
1
19

Chapter 7

OBSERVATION & CONCLUSION

7 Observations & Conclusion

7.1 Training on complete dataset

Algorithm	MAE
Linear Regression	94.9482172761933 8
SVR	127.7407386020383 9
Artificial neural nets	85.264871352886 5

- Various visualizations of data are observed which helps in implementing the approaches for prediction.
- Observations indicates machine learning models won't work well for prediction of rainfall due to fluctuations in rainfall.
- 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.
- Approximately close means, noticed less standard deviations.

Chapter 8

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