Introduction

Support Vector Machine is a supervised Machine Learning algorithm widely used for solving different machine learning problems. Given a dataset, the algorithm tries to divide the data using hyperplanes and then makes the predictions. SVM is a non-probabilistic linear classifier. While other classifiers, when classifying, predict the probability of a data point to belong to one group or the another, SVM directly says to which group the datapoint belongs to without using any probability calculation.

Understanding the Mathematics involved

Let’s take the example of the following dataset and see how can we divide the data into appropriate groups.

We can see that there are two groups of data. The question is how to divide these points into two groups. It can be done using any of the three lines. Or, for that purpose, there can be an infinite number of straight lines that can divide these points into two classes. Now, which line to choose? SVM solves this problem using the maximum margin as shown

The black line in the middle is the optimum classifier. This line is drawn to maximise the distance of the classifier line from the nearest points in the two classes. It is also called a **hyperplane** in terms of SVM. A *Hyperplane* is an n-1 dimensional plane which optimally divides the data of n dimensions. Here, as we have only a 2-D data, so the hyperplane can be represented using one dimension only. Hence, the hyperplane is a line here. The two points (highlighted with circles) which are on the yellow lines, they are called the **support vectors**. As it is a 2-D figure, they are points. In a multi-dimensional space, they will be vectors, and hence, the name- support vector machine as the algorithm creates the optimum classification line by maximising its distance from the two support vectors.

When the data is not linearly separable, then to create a hyperplane to separate data into different groups, the SVM algorithm needs to perform computations in a higher-dimensional space. But the introduction of new dimensions makes the computations for the SVMs more intensive, which impacts the algorithm performance. To rectify this, mathematicians came up with the approach of Kernel methods. Kernel methods use kernel functions available in mathematics. The unique feature of a kernel function is to compute in a higher-dimensional space without calculating the new coordinates in that higher dimension. It implicitly uses predefined mathematical functions to do operations on the existing points which mimic the computation in a higher-dimensional space without adding to the computation cost as they are not actually calculating the coordinates in the higher dimension thereby avoiding the computation of calculating distances from the newly computed points. This is called the kernel trick.

Image: bogotobogo.com

In the left diagram above, we have a non-linear distribution of data as we can not classify a data using a linear equation. To solve this problem, we can project the points in a 3-dimensional space and then derive a plane which divides the data into two parts. In theory, that’s what a kernel function does without computing the additional coordinates for the higher dimension.

Python Implementation

In [1]:

```python
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:

```python
df=pd.read_csv('winequality-red.csv')
```

In [3]:

```python
df.head()
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoh
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9

In [14]:

```python
df.isna().sum()
```

Out[14]:

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

As the data consists of values which differ a lot in magnitude, they need to be brought to the same scale. It's done using the standard scalar.

In [4]:

```python
from sklearn.preprocessing import StandardScaler
scaler= StandardScaler()
new_data=scaler.fit_transform(df.drop(labels=['quality'],axis=1))
```

In [5]:

```
df.columns
```

Out[5]:

```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual s
ugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'de
nsity',
       'pH', 'sulphates', 'alcohol', 'quality'],
      dtype='object')
```

In [6]:

```
columns=['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol']
```

In [7]:

```
new_df=pd.DataFrame(data=new_data,columns=columns)
```

In [8]:

```
new_df.head()
```

Out[8]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	
0	-0.528360	0.961877	-1.391472	-0.453218	-0.243707	-0.466193	-0.379133	0.558274	1.2886
1	-0.298547	1.967442	-1.391472	0.043416	0.223875	0.872638	0.624363	0.028261	-0.7199
2	-0.298547	1.297065	-1.186070	-0.169427	0.096353	-0.083669	0.229047	0.134264	-0.3311
3	1.654856	-1.384443	1.484154	-0.453218	-0.264960	0.107592	0.411500	0.664277	-0.9791
4	-0.528360	0.961877	-1.391472	-0.453218	-0.243707	-0.466193	-0.379133	0.558274	1.2886

As there are no missing values, we don't need to do data imputation.

In [9]:

```
x=new_df
y=df['quality']
```

In [10]:

```
from  sklearn.model_selection import train_test_split
train_x,test_x,train_y,test_y=train_test_split(x,y,test_size=0.33, random_state
```

In [11]:

```
from sklearn.svm import SVC
```

In [12]:

```
model=SVC()
model.fit(train_x,train_y)
```

Out[12]:

```
SVC(C=1.0, break_ties=False, cache_size=200, class_weight=None, coef0=
0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rb
f',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

In [14]:

```
model.predict(test_x)
```

Out[14]:

```
array([5, 5, 6, 5, 6, 5, 5, 5, 6, 6, 6, 5, 6, 5, 5, 7, 5, 6, 7, 5, 5,
5,
       6, 6, 5, 5, 6, 5, 5, 6, 5, 5, 6, 5, 6, 5, 6, 6, 5, 6, 5, 5, 6,
5,
       6, 6, 6, 6, 5, 6, 5, 5, 6, 7, 5, 5, 6, 5, 6, 5, 6, 6, 5, 5, 6,
5,
       6, 5, 7, 5, 6, 5, 6, 6, 6, 5, 7, 5, 6, 7, 5, 7, 5, 5, 6, 6, 5,
6,
       6, 5, 6, 5, 5, 6, 5, 6, 5, 6, 5, 5, 5, 5, 6, 6, 6, 6, 6, 5, 6,
5,
       6, 5, 6, 5, 6, 6, 6, 5, 5, 6, 6, 6, 6, 5, 5, 5, 6, 6, 5, 6, 6,
5,
       5, 6, 6, 5, 5, 5, 5, 6, 6, 6, 6, 5, 6, 5, 6, 5, 6, 5, 6, 6, 5,
6,
       6, 6, 5, 6, 5, 6, 7, 6, 6, 5, 5, 6, 5, 5, 5, 5, 5, 5, 6, 5, 7,
6,
       6, 5, 5, 5, 5, 7, 5, 7, 5, 6, 6, 6, 7, 5, 6, 6, 5, 6, 6, 5, 5,
5,
       6, 6, 5, 5, 5, 5, 7, 6, 5, 5, 6, 6, 7, 5, 6, 6, 6, 6, 6, 5, 6,
5,
       5, 6, 6, 6, 5, 5, 5, 7, 5, 5, 5, 5, 6, 6, 5, 6, 5, 6, 6, 5, 5,
5,
       6, 6, 5, 6, 6, 5, 6, 5, 6, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 5,
7,
       6, 7, 6, 5, 6, 6, 5, 6, 5, 5, 5, 5, 6, 6, 6, 5, 7, 5, 5, 5, 5,
6,
       5, 6, 5, 6, 5, 7, 6, 5, 5, 6, 5, 6, 6, 7, 5, 5, 6, 5, 5, 5, 6,
6,
       6, 7, 5, 5, 6, 5, 5, 6, 5, 5, 6, 5, 6, 5, 6, 5, 5, 5, 6, 5, 5,
6,
       6, 7, 5, 5, 6, 6, 6, 6, 5, 5, 6, 7, 5, 5, 6, 5, 6, 5, 6, 6, 6,
6,
       5, 5, 6, 6, 5, 5, 5, 5, 5, 5, 5, 6, 5, 6, 6, 5, 5, 5, 5, 5, 6,
6,
       5, 6, 5, 6, 5, 5, 5, 6, 6, 5, 6, 6, 6, 5, 5, 6, 5, 5, 5, 6, 6,
6,
       7, 6, 5, 6, 5, 5, 6, 5, 5, 6, 7, 6, 5, 5, 6, 7, 6, 6, 6, 6, 5,
7,
       5, 6, 6, 5, 5, 5, 6, 6, 5, 5, 6, 5, 7, 5, 5, 5, 6, 5, 5, 5, 5,
6,
       6, 6, 6, 5, 5, 5, 5, 6, 6, 5, 6, 6, 5, 5, 5, 6, 7, 6, 6, 5, 5,
5,
       5, 5, 6, 5, 5, 5, 5, 6, 7, 6, 6, 6, 5, 6, 6, 6, 6, 5, 6, 6, 6,
6,
       5, 6, 6, 6, 5, 5, 6, 6, 5, 5, 6, 5, 6, 5, 5, 5, 5, 5, 5, 5, 5,
5,
       6, 6, 6, 6, 6, 6, 5, 5, 5, 7, 6, 6, 6, 5, 5, 5, 6, 6, 7, 7, 5,
5],
      dtype=int64)
```

In [20]:

```
from sklearn.metrics import accuracy_score
```

In [16]:

```
accuracy_score(test_y,model.predict(test_x))
```

Out[16]:

```
0.6003787878787878
```

As observed, the accuracy of the model is quite low. We need to implement the grid search approach to optimize the parameters to give the best accuracy.

Implementing Grid Search

In [13]:

```
from sklearn.model_selection import GridSearchCV
```

In [14]:

```
param_grid={'C':[0.1,1,10,50,100,500],'gamma':[1,0.5,0.1,0.01,0.001]}
```

In [44]:

```
grid= GridSearchCV(SVC(),param_grid, verbose=3, n_jobs=-1)
```

In [45]:

```
grid.fit(train_x,train_y)
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
[CV] C=0.1, gamma=1
..................................................
[CV] ........................ C=0.1, gamma=1, score=nan, total=   0.
0s
[CV] C=0.1, gamma=1
..................................................
[CV] ........................ C=0.1, gamma=1, score=nan, total=   0.
0s
[CV] C=0.1, gamma=1
..................................................
[CV] ........................ C=0.1, gamma=1, score=nan, total=   0.
0s
[CV] C=0.1, gamma=1
..................................................
[CV] ........................ C=0.1, gamma=1, score=nan, total=   0.
0s
[CV] C=0.1, gamma=1
..................................................
[CV] ........................ C=0.1, gamma=1, score=nan, total=   0.
```

In [17]:

```
grid.best_params_
```

Out[17]:

```
{'C': 10, 'gamma': 1}
```

In [18]:

```
model_new=SVC(C=10, gamma=1)
model_new.fit(train_x,train_y)
```

Out[18]:

```
SVC(C=10, break_ties=False, cache_size=200, class_weight=None, coef0=
0.0,
    decision_function_shape='ovr', degree=3, gamma=1, kernel='rbf', ma
x_iter=-1,
    probability=False, random_state=None, shrinking=True, tol=0.001,
    verbose=False)
```

In [21]:

```
accuracy_score(test_y,model_new.predict(test_x))
```

Out[21]:

```
0.6268939393939394
```

Support Vector Regression

Let’s talk about Linear Regression first. How to determine the best fit line? The idea is to create a line which minimises the total residual error. The SVR approach is a bit different. Instead of trying to minimise the error, SVR focuses on keeping the error in a fixed range. This approach can be explained using three lines. The first line is the best fit regressor line, and the other two lines are the bordering ones which denote the range of error.

What does this mean? It means that we are going to consider the points inside this ± error boundary only for preparing our model. In other words, the best fit line(or the hyperplane) will be the line which goes through the maximum number of data points and the error boundaries are chosen to ensure maximum inclusion. This error term can be customized using the '_epsilon_' parameter defined for the scikit-learn SVR implementation.

Python Implementation

In [22]:

```
# necessary Imports
import pandas as pd
import matplotlib.pyplot as plt
% matpllotlib inline
```

```
UsageError: Line magic function `%` not found.
```

In [23]:

```
df= pd.read_csv('Admission_Prediction.csv')
```

In [24]:

```
df.head()
```

Out[24]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337.0	118.0	4.0	4.5	4.5	9.65	1	0.92
1	2	324.0	107.0	4.0	4.0	4.5	8.87	1	0.76
2	3	NaN	104.0	3.0	3.0	3.5	8.00	1	0.72
3	4	322.0	110.0	3.0	3.5	2.5	8.67	1	0.80
4	5	314.0	103.0	2.0	2.0	3.0	8.21	0	0.65

In [25]:

```
df.isna().sum()
```

Out[25]:

```
Serial No.            0
GRE Score            15
TOEFL Score          10
University Rating    15
SOP                   0
LOR                   0
CGPA                  0
Research              0
Chance of Admit       0
dtype: int64
```

As we can see, there are some column with missing values. we need to impute those missing values.

In [26]:

```
df['GRE Score'].fillna(df['GRE Score'].mean(),inplace=True)
df['TOEFL Score'].fillna(df['TOEFL Score'].mean(),inplace=True)
df['University Rating'].fillna(df['University Rating'].mode()[0],inplace=True)
```

In [27]:

```
# seeing that after imputation no column has missing values
df.isna().sum()
```

Out[27]:

```
Serial No.           0
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

In [28]:

```
x=df.drop(['Chance of Admit','Serial No.'],axis=1)
y=df['Chance of Admit']
columns=x.columns
```

In [29]:

```
from sklearn.model_selection import train_test_split
```

In [30]:

```
train_x,test_x,train_y,test_y=train_test_split(x,y,test_size=0.33, random_state
```

In [31]:

```
from sklearn.svm import SVR
svr= SVR(C=10)
```

In [ ]:

```

```

```

```

In [32]:

```
svr.fit(train_x, train_y)
```

Out[32]:

```
SVR(C=10, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma='sca
le',
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=Fals
e)
```

In [33]:

```
from sklearn.metrics import r2_score
score= r2_score(test_y,svr.predict(test_x))
score
```

Out[33]:

```
0.7340987165302327
```

In [34]:

```
from sklearn.model_selection import GridSearchCV
param_grid={'C':[0.1,1,10,50,100,500],'gamma':[1,0.5,0.1,0.01,0.001] }
grid= GridSearchCV(SVR(),param_grid, verbose=3)
```

In [35]:

```
grid.fit(train_x,train_y)
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
[CV] C=0.1, gamma=1
..................................................
[CV] ...................... C=0.1, gamma=1, score=0.092, total=   0.
0s
[CV] C=0.1, gamma=1
..................................................
[CV] ...................... C=0.1, gamma=1, score=0.126, total=   0.
0s
[CV] C=0.1, gamma=1
..................................................
[CV] ...................... C=0.1, gamma=1, score=0.079, total=   0.
0s
[CV] C=0.1, gamma=1
..................................................
[CV] ...................... C=0.1, gamma=1, score=0.089, total=   0.
0s
[CV] C=0.1, gamma=1
..................................................
[CV]                        C=0.1, gamma=1, score=0.054, total=   0.
```

In [36]:

```
grid.best_estimator_
```

Out[36]:

```
SVR(C=50, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma=0.00
1,
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=Fals
e)
```

In [37]:

```
svr_new=SVR(C=50, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma=0.001
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
```

In [38]:

```
svr_new.fit(train_x, train_y)
```

Out[38]:

```
SVR(C=50, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma=0.00
1,
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=Fals
e)
```

In [39]:

```
score_new= r2_score(test_y,svr_new.predict(test_x))
score_new
```

Out[39]:

```
0.7457021772643664
```

In [58]:

```
# saving the model to the local file system
"""from joblib import dump, load
filename = 'test1.joblib'
dump(svr_new, filename) """
filename = 'finalized_model.pickle'
pickle.dump(svr_new, open(filename, 'wb'))
```

Out[58]:

```
['test1.joblib']
```

Now this saved model file will be used for prediction. We'll create a Flask app for the same and deploy it to AWS.

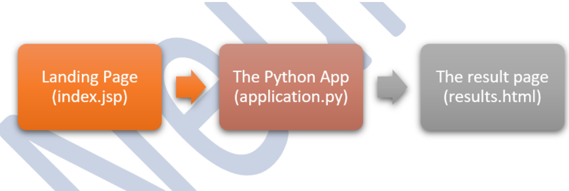
In [179]:

```
loaded_model = pickle.load(open(filename, 'rb'))
prediction=loaded_model.predict(([[320,120,5,5,5,10,1]]))
print(prediction[0])
```

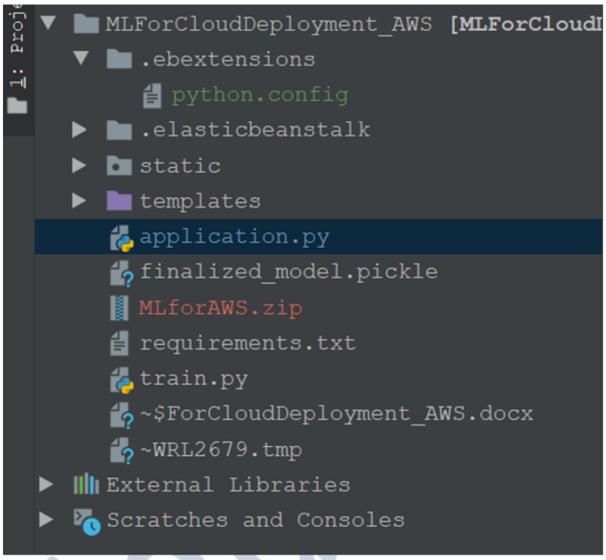
```
0.9514405802107618
```

Flask App

As we'll expose the created model as a web API to be consumed by the client/client APIs, we'd do it using the flask framework. The flow of our flask app will be:



- Create the project structure, as shown below:



```
▼ MLForCloudDeployment_AWS [MLForCloudI
    ▼ .ebextensions
          python.config
    ▶ .elasticbeanstalk
    ▶ static
    ▶ templates
      application.py
      finalized_model.pickle
      MLforAWS.zip
      requirements.txt
      train.py
      ~$ForCloudDeployment_AWS.docx
      ~WRL2679.tmp
▶ External Libraries
▶ Scratches and Consoles
```

```
* Index.html

{% extends 'base.html' %}

{% block head %}

<title>Search Page</title>
<link rel="stylesheet" href="{{ url_for('static', filename='css/style.css') }}">
{% endblock %}

{% block body %}
<div class="content">
    <h1 style="text-align: center">Predict Your chances for Admission</h1>

    <div class="form">
        <form action="/predict" method="POST">
            <input type="number" name="gre_score" id="gre_score" placeholder="GRE Score">
            <input type="number" name="toefl_score" id="toefl_score" placeholder="TOEFL Score">
            <input type="number" name="university_rating" id="university_rating" placeholder="University Rating">
            <input type="number" name="sop" id="sop" placeholder="SOP Score">
            <input type="number" name="lor" id="lor" placeholder="LOR Score">
            <input type="number" name="cgpa" id="cgpa"placeholder="CGPA" step="any">
            <select name="research" id="research">
  <option value="yes">Yes</option>
  <option value="no">No</option>
</select>
            <input type="submit" value="Predict">
        </form>
    </div>
</div>
{% endblock %}

```

```
* application.py

# importing the necessary dependencies
from flask import Flask, render_template, request,jsonify
from flask_cors import CORS,cross_origin
```

```
import pickle

app = Flask(__name__) # initializing a flask app

@app.route('/',methods=['GET'])  # route to display the home page
@cross_origin()
def homePage():
    return render_template("index.html")

@app.route('/predict',methods=['POST','GET']) # route to show the predictions in a web UI
@cross_origin()
def index():
    if request.method == 'POST':
        try:
            #  reading the inputs given by the user
            gre_score=float(request.form['gre_score'])
            toefl_score = float(request.form['toefl_score'])
            university_rating = float(request.form['university_rating'])
            sop = float(request.form['sop'])
            lor = float(request.form['lor'])
            cgpa = float(request.form['cgpa'])
            is_research = request.form['research']
            if(is_research=='yes'):
                research=1
            else:
                research=0
            filename = 'finalized_model.pickle'
            loaded_model = pickle.load(open(filename, 'rb')) # loading the model file from the storage
            # predictions using the loaded model file
            prediction=loaded_model.predict([[gre_score,toefl_score,university_rating,sop,lor,cgpa,research]])
            print('prediction is', prediction)
            # showing the prediction results in a UI
            return render_template('results.html',prediction=round(100*prediction[0]))
        except Exception as e:
            print('The Exception message is: ',e)
            return 'something is wrong.'
    # return render_template('results.html')
    else:
        return render_template('index.html')



if __name__ == "__main__":
    #app.run(host='127.0.0.1', port=8001, debug=True)
   app.run(debug=True) # running the app

```

```
* results.html

•   <!DOCTYPE html>
<html lang="en" >

<head>
  <meta charset="UTF-8">
  <title>Review Page</title>
```

```

    <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/normalize/5.0.0/normalize.min.css">


      <link rel="stylesheet" href="./style.css">
    <link rel="stylesheet" href="{{ url_for('static', filename='css/style.css') }}">


</head>

<body>

  <div class="table-users">
   <div class="header">Prediction</div>

      <p>Your chance for admission is {{prediction}} percent</p>
</div>



</body>

</html>
```

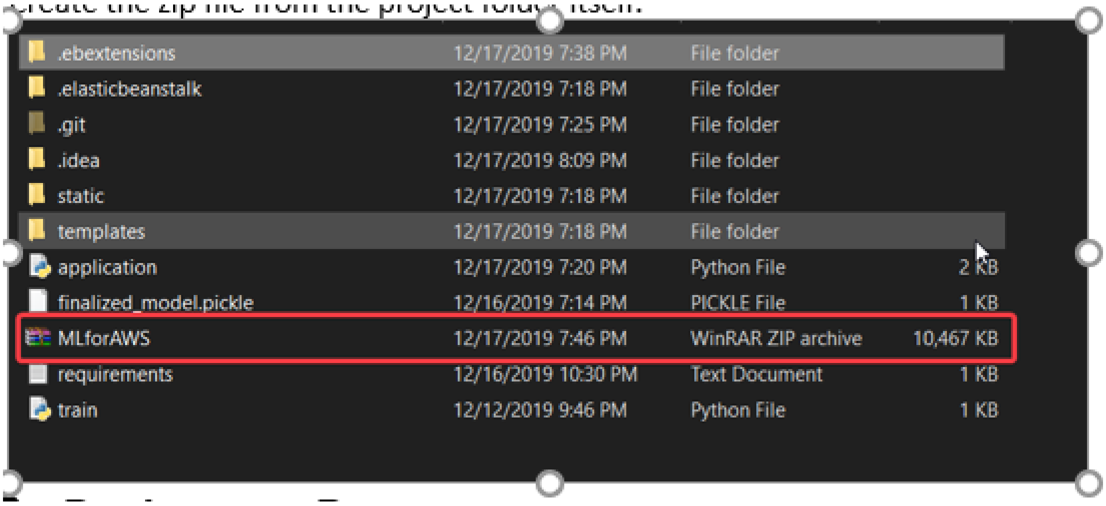
```
* python.config

option_settings:
  "aws:elasticbeanstalk:container:python":
    WSGIPath: application.py

```

Deployment to AWS:

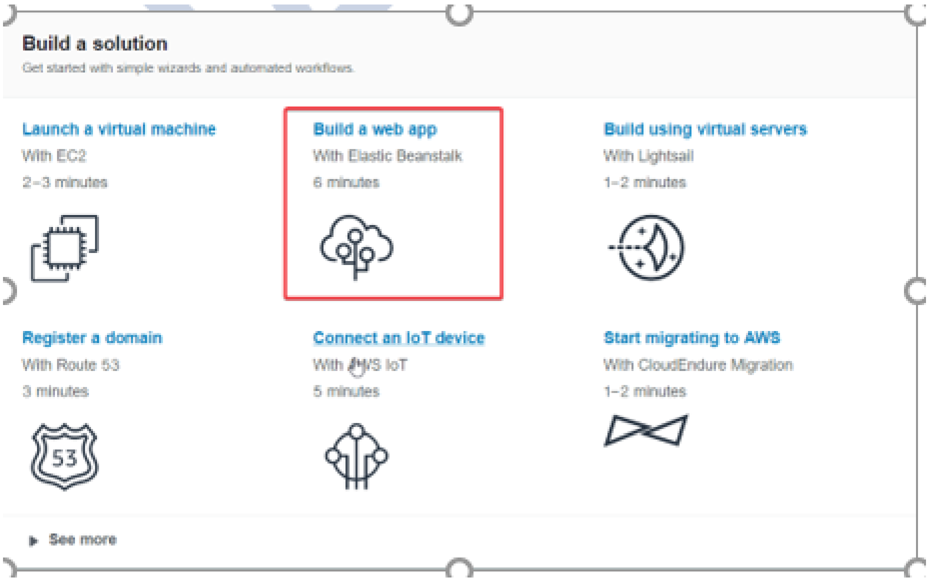
• The python application file should be named application.py • Create a requirements.txt using pip freeze > requirements.txt from the project folder • Create a folder '.ebextensions' and create a file 'python.config' inside it. Make sure to populate the content of python.config, as shown above. • Create the zip file from the project folder itself.



.ebextensions	12/17/2019 7:38 PM	File folder	
.elasticbeanstalk	12/17/2019 7:18 PM	File folder	
.git	12/17/2019 7:25 PM	File folder	
.idea	12/17/2019 8:09 PM	File folder	
static	12/17/2019 7:18 PM	File folder	
templates	12/17/2019 7:18 PM	File folder	
application	12/17/2019 7:20 PM	Python File	2 KB
finalized_model.pickle	12/16/2019 7:14 PM	PICKLE File	1 KB
MLforAWS	12/17/2019 7:46 PM	WinRAR ZIP archive	10,467 KB
requirements	12/16/2019 10:30 PM	Text Document	1 KB
train	12/12/2019 9:46 PM	Python File	1 KB

Deployment Process

• Go to https://aws.amazon.com/ (https://aws.amazon.com/) and create an account if already don't have one. • Go to the console and go to the 'Build a web app' section and click it.



Build a solution

Get started with simple wizards and automated workflows.

Launch a virtual machine
With EC2
2–3 minutes

Build a web app
With Elastic Beanstalk
6 minutes

Build using virtual servers
With Lightsail
1–2 minutes

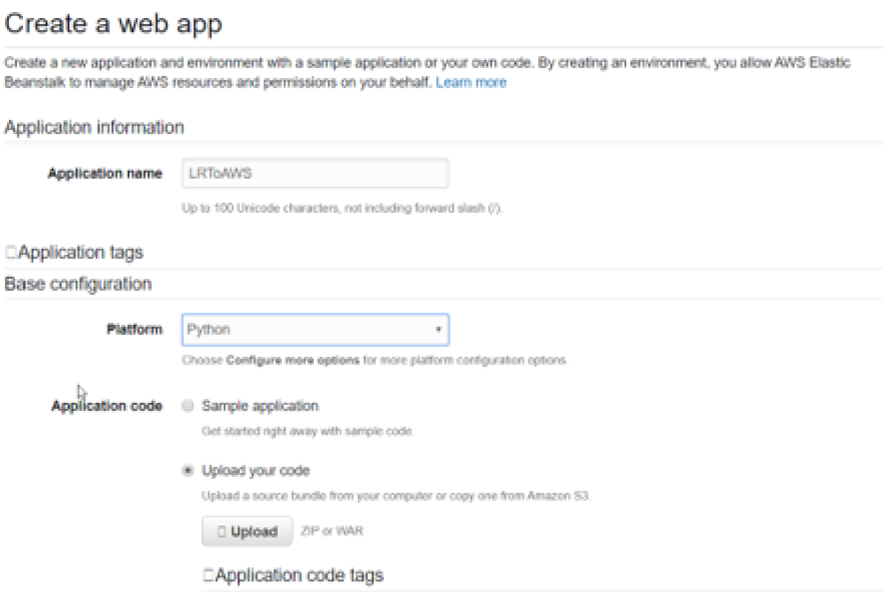
Register a domain
With Route 53
3 minutes

Connect an IoT device
With AWS IoT
5 minutes

Start migrating to AWS
With CloudEndure Migration
1–2 minutes

▸ See more

• Give the name of the application, give platform as python, and select the option to upload your code from ZIP.



Create a web app

Create a new application and environment with a sample application or your own code. By creating an environment, you allow AWS Elastic Beanstalk to manage AWS resources and permissions on your behalf. Learn more

Application information

Application name: LRToAWS

Up to 100 Unicode characters, not including forward slash (/).

Application tags

Base configuration

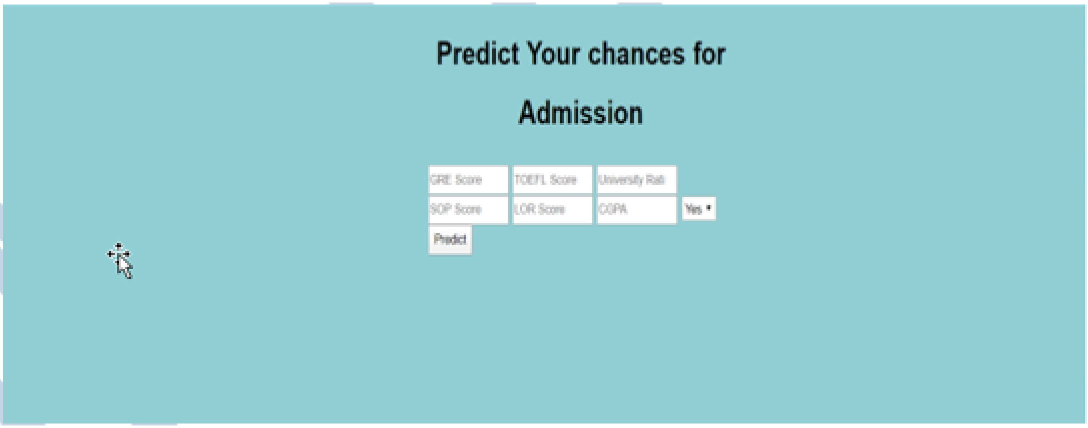
Platform: Python

Choose **Configure more options** for more platform configuration options.

Application code:
○ Sample application
Get started right away with sample code.
● Upload your code
Upload a source bundle from your computer or copy one from Amazon S3.
Upload ZIP or WAR

Application code tags

Final Result:



Predict Your chances for

Admission