Create a complete Machine learning web application using React and Flask

Karan Bhanot

Apr 16 · 6 min read ★

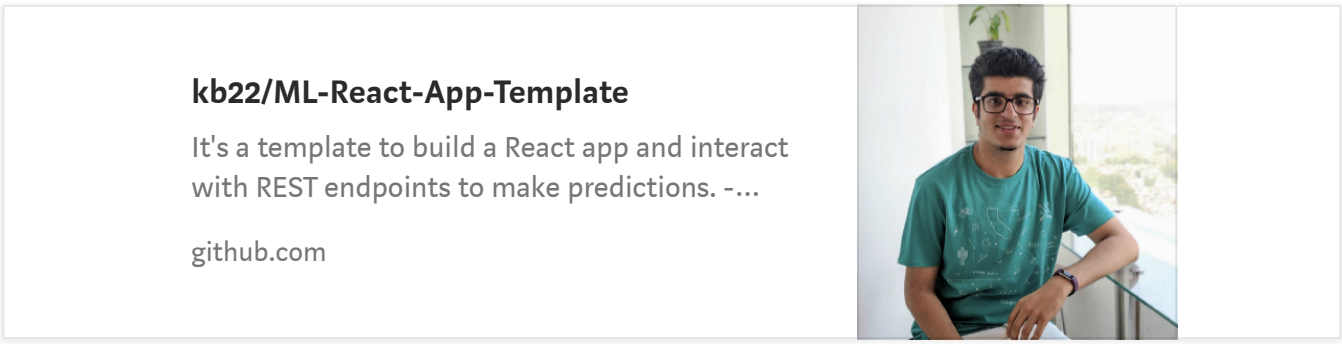
Photo by Alvaro Reyes on Unsplash

I have always wanted to develop a complete Machine learning application where I would have a UI to feed in some inputs and the Machine learning model to predict on those values. Last week, I did just that. In the process, I created an easy to use template in React and Flask, that anyone can modify to create their own application in a matter of minutes.

Highlights of the project:

1. The front-end is developed in React and would include a single page with a form to submit the input values
2. The back-end is developed in Flask which exposes prediction endpoints to predict using a trained classifier and send the result back to the front-end for easy consumption

The GitHub repo is below. Fork the project and create your own application today!



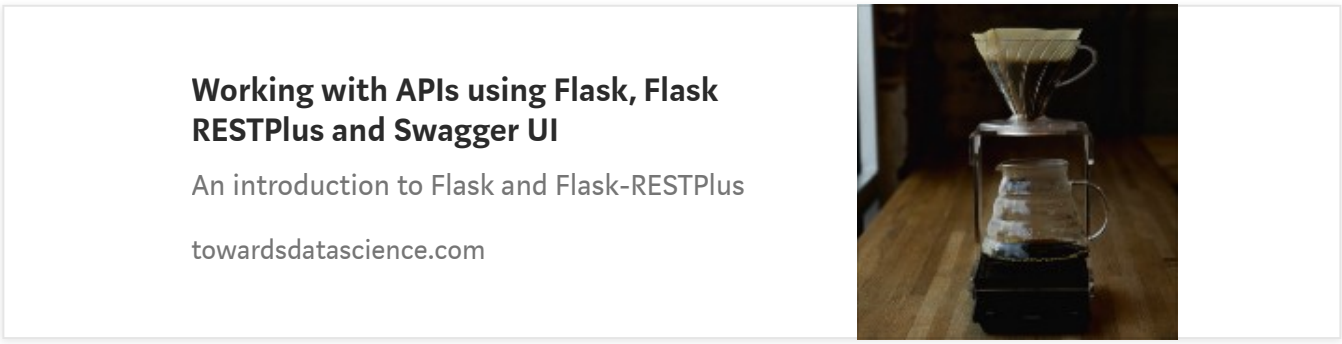
Template

React

React is a JavaScript library created by Facebook to help make working with User interfaces simple and easy to develop and use. It's one of the leading languages for front-end development. You can read about it here. The best resource to learn about React is its documentation itself which is very comprehensive and easy to grasp.

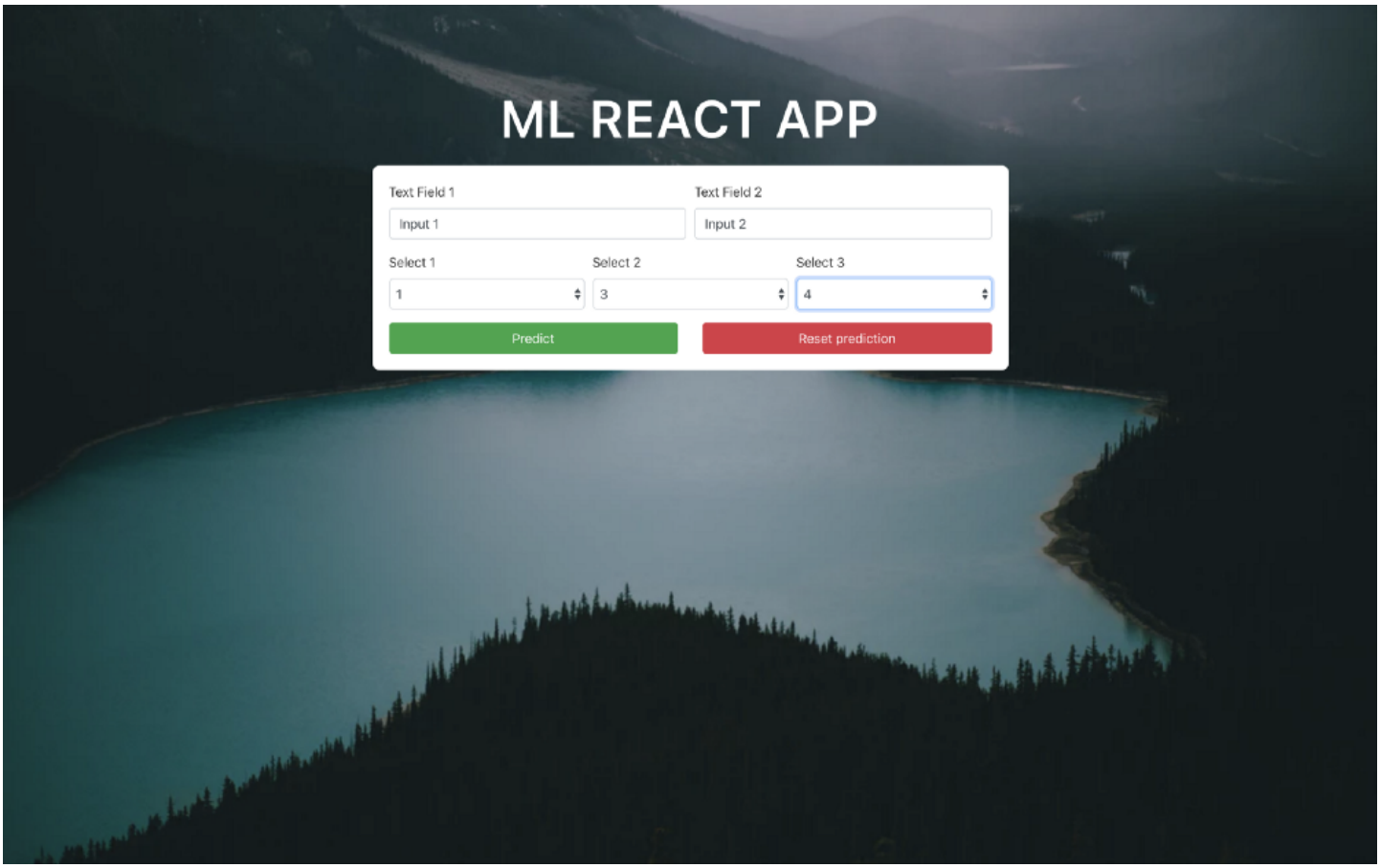
Flask and Flask-RESTPlus

Flask and Flask-RESTPlus allow us to define a service in Python which will have endpoints which we can call from the UI. You can learn more about developing a Flask app from my article below.



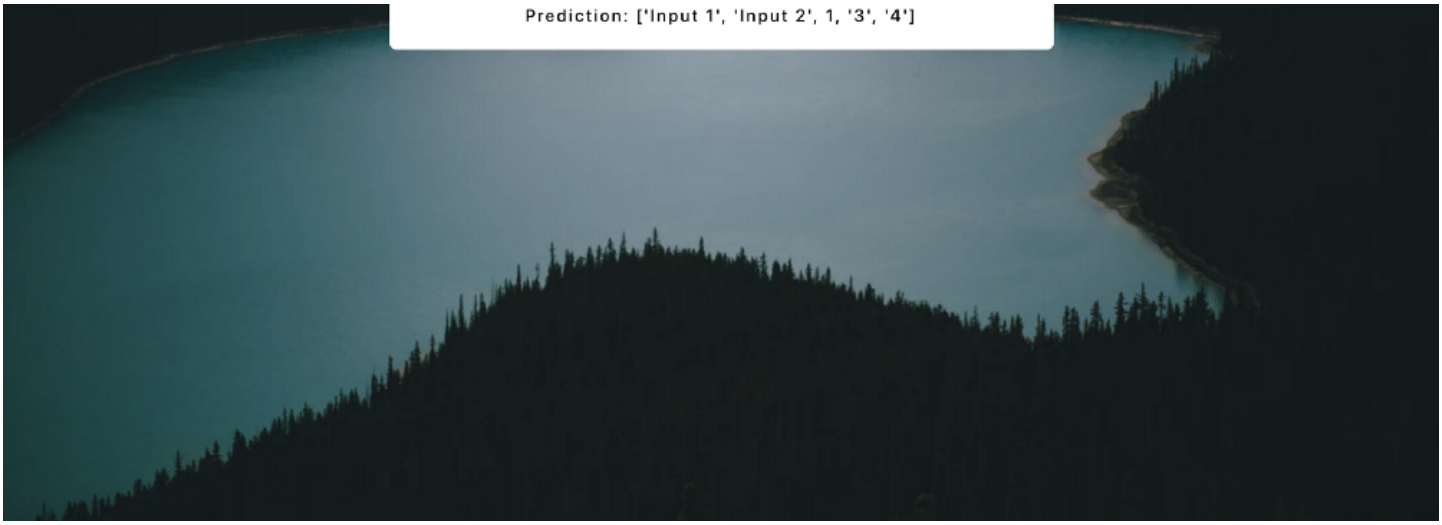
Description

I used `create-react-app` to create a basic React app to begin with. Next, I loaded `bootstrap` which allows us to create responsive websites for each screen size. I updated the `App.js` file to add a form with dropdowns and `Predict` and `Reset Prediction` buttons. I added each form property to state and on pressing the `Predict` button, I send the data to the Flask backend. I also updated the `App.css` file to add style to the page.



Template view

The Flask app has a POST endpoint `/prediction`. It accepts the input values as a json, converts it into an array and returns to the UI. In actual application, we'll use the same data to make prediction using the classifier stored in `classifier.joblib` and return the prediction.



Prediction displayed on UI

`Reset Prediction` will remove the prediction from the UI.

Starting the template

Clone the repo to your computer and go inside it and open two terminals here.

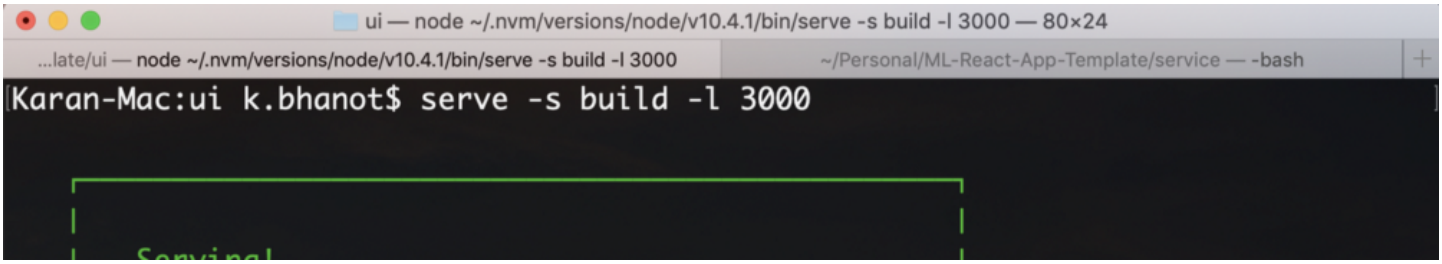
Preparing the UI

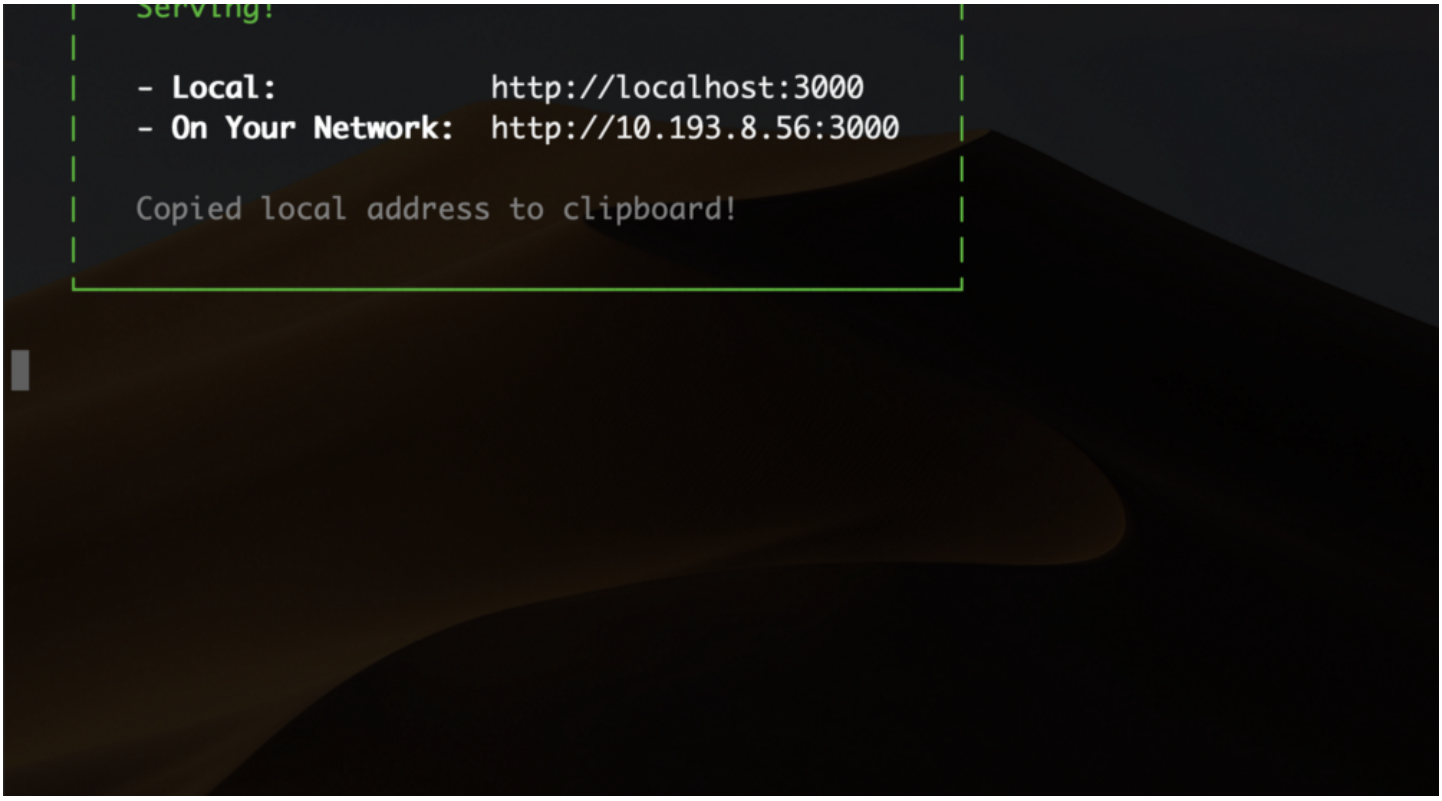
In the first terminal, go inside the `ui` folder using `cd ui`. Make sure you are using the node version `10.4.1`. Once inside the folder, run the command `yarn install` to install all dependencies.

To run the UI on server, we will use `serve`. We will begin by installing the `serve` globally, post which, we'll build our application and then finally run the UI using `serve` on port 3000.

```
npm install -g serve
npm run build
serve -s build -l 3000
```

You can now go to `localhost:3000` to see that the UI is up and running. But it won't interact with the Flask service which is still not up. So, let's do that.





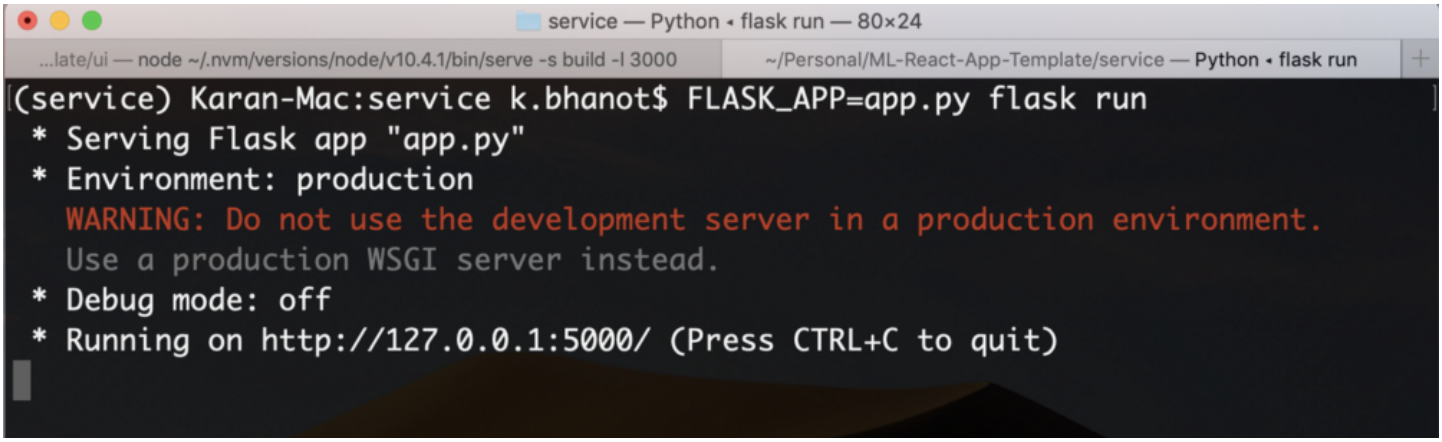
UI

Preparing the service

On the second terminal, move inside the `service` folder using `cd service`. We begin by creating a virtual environment using `virtualenv` and Python 3. You can read about virtualenv here. We will then install all the required dependencies using pip after activating the environment. Finally, we'll run the Flask app.

```
virtualenv -p Python3 .
source bin/activate
pip install -r requirements.txt
FLASK_APP=app.py flask run
```

This will start up the service on `127.0.0.1:5000`.



Service

Voila! The complete application will now be working properly. Yaay!!

Using the template for own use case

To understand the process of using the template for any model, I'll use the `iris` dataset and create a model for the same. This example is also available in the `example` folder in the project.

Create the model

I trained a `DecisionTreeClassifier` on the iris dataset which requires 4 features — Sepal Length, Sepal Width, Petal Length and Petal Width. Then, I saved the model to `classifier.joblib` using `joblib.dump()`. The classifier can now be used to predict on new data.

Update the service

Next, I opened the file `app.py` in a text editor (Sublime Text is one). I uncommented the line `classifier = joblib.load('classifier.joblib')` so that the variable `classifier` now holds the trained model.

In the post method, I made the following updates:

```
prediction = classifier.predict(np.array(data).reshape(1, -1))
types = { 0: "Iris Setosa", 1: "Iris Versicolour ", 2: "Iris Virginica"}
response = jsonify({
                                "statusCode": 200,
                                "status": "Prediction made",
                                "result": "The type of iris plant is: " + types[prediction[0]]
```

```
                                    })
```

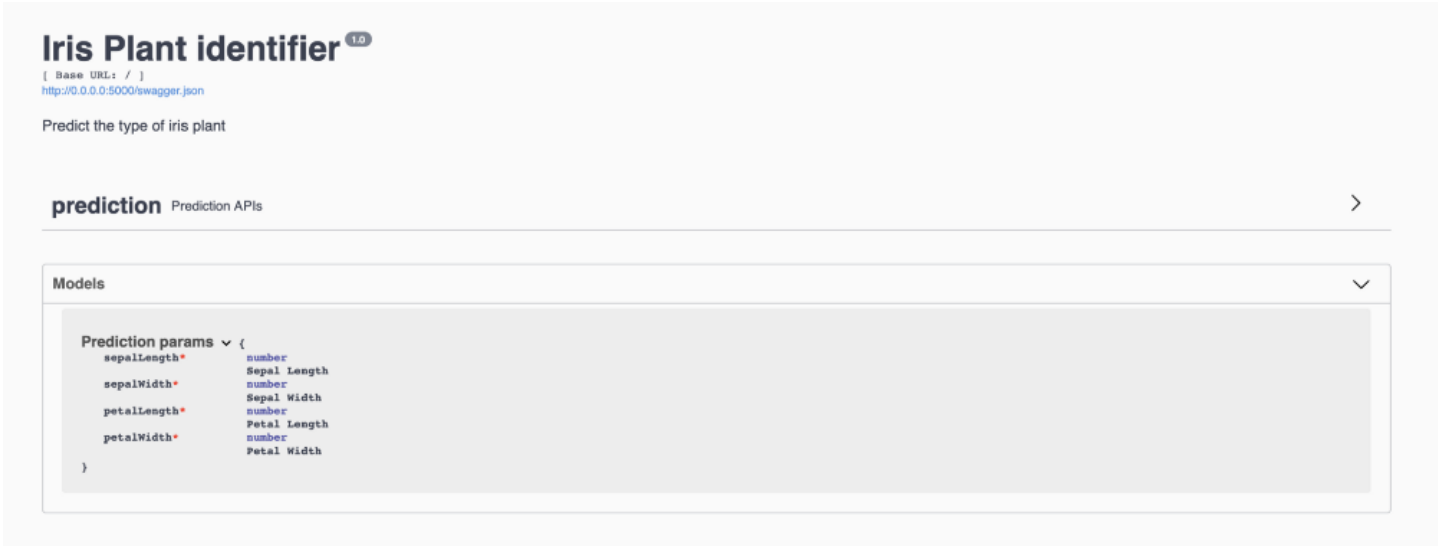
Firstly, I used `classifier.predict()` to get the prediction. Next, I created a map for the classes such that 0 means `Iris Setosa`, 1 means `Iris Versicolour` and 2 means `Iris Virginica`. I finally returned the prediction in the `result` key.

Update: As pointed out by Martins Untals, I forgot to mention that we also need to update the model so that it works correctly and has the updated model in Swagger UI.

```
model = app.model('Prediction params',
                                  {'sepalLength': fields.Float(required = True,
                                                               desc
                                                               help="Sepal
                                   'sepalWidth': fields.Float(required = True,
                                                               desc
                                                               help="Sepal
                                   'petalLength': fields.Float(required = True,
                                                               descrip
                                                               help="Petal Ler
                                   'petalWidth': fields.Float(required = True,
                                                               descrip
                                                               help="Petal Wic
```

update_model.py hosted with ♡ by GitHub view raw

As can be seen in the gist, I've updated the field names, their type to `Float`, description and help text. The same will now be reflected in Swagger too.



Updated model in Swagger UI

Update the UI

The form is made up of columns inside rows. Thus, as I have 4 features, I added 2 columns in 2 rows. The first row will have dropdowns for Sepal Length and Sepal Width. The second row will have dropdowns for Petal Length and Petal Width.

I began by creating a list of options for each of these dropdowns.

```
var sepalLengths = []
for (var i = 4; i <= 7; i = +(i + 0.1).toFixed(1)) {
  sepalLengths.push(<option key = {i} value = {i}>{i}</option>);
}
var sepalWidths = []
for (var i = 2; i <= 4; i = +(i + 0.1).toFixed(1)) {
  sepalWidths.push(<option key = {i} value = {i}>{i}</option>);
}
var petalLengths = []
for (var i = 1; i <= 6; i = +(i + 0.1).toFixed(1)){
  petalLengths.push(<option key = {i} value = {i}>{i}</option>);
}
var petalWidths = []
for (var i = 0.1; i <= 3; i = +(i + 0.1).toFixed(1)) {
  petalWidths.push(<option key = {i} value = {i}>{i}</option>);
}
```

dropdownOptions.js hosted with ♡ by GitHub view raw

Next, I defined two rows with two columns each. Each dropdown selection will look like the code below:

```
<Form.Group as={Col}>
  <Form.Label>Petal Length</Form.Label>
  <Form.Control
    as="select"
    value={formData.petalLength}
    name="petalLength"
    onChange={this.handleChange}>
    {petalLengths}
  </Form.Control>
</Form.Group>
```

selection.js hosted with ♡ by GitHub view raw

For each dropdown, we'll have to update the text inside `<Form.Label></Form.Label>`. We'll name each selection group as well. Let's say the name be `petalLength` so we set the value as `{formData.petalLength}` and name as `"petalLength"`. The options are added using the names we defined above inside `<Form.Control></Form.Control>` as we can see `{petalLengths}` above. Two such groups inside a `<Form.Row></Form.Row>` will make our UI.

The state must also be updated with the same names inside `formData` with the default values as the smallest value of the respective dropdowns. The constructor will look like below. As you can see, the state has been updated to have `formData` with new keys.

```
constructor(props) {
  super(props);

  this.state = {
    isLoading: false,
    formData: {
      sepalLength: 4,
      sepalWidth: 2,
      petalLength: 1,
      petalWidth: 0
    },
    result: ""
  };
}
```

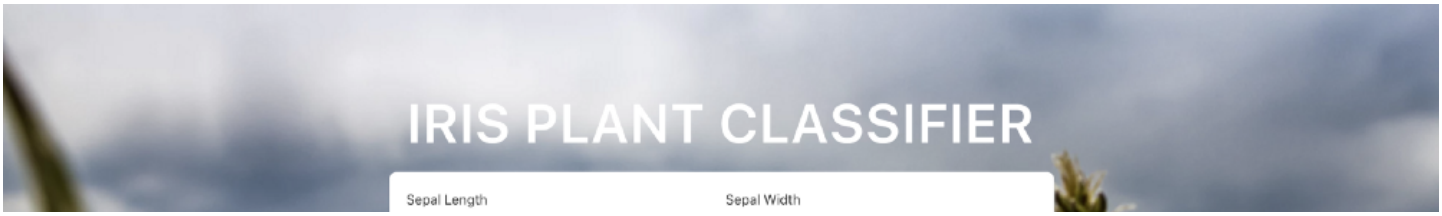
constructor.js hosted with ♡ by GitHub view raw

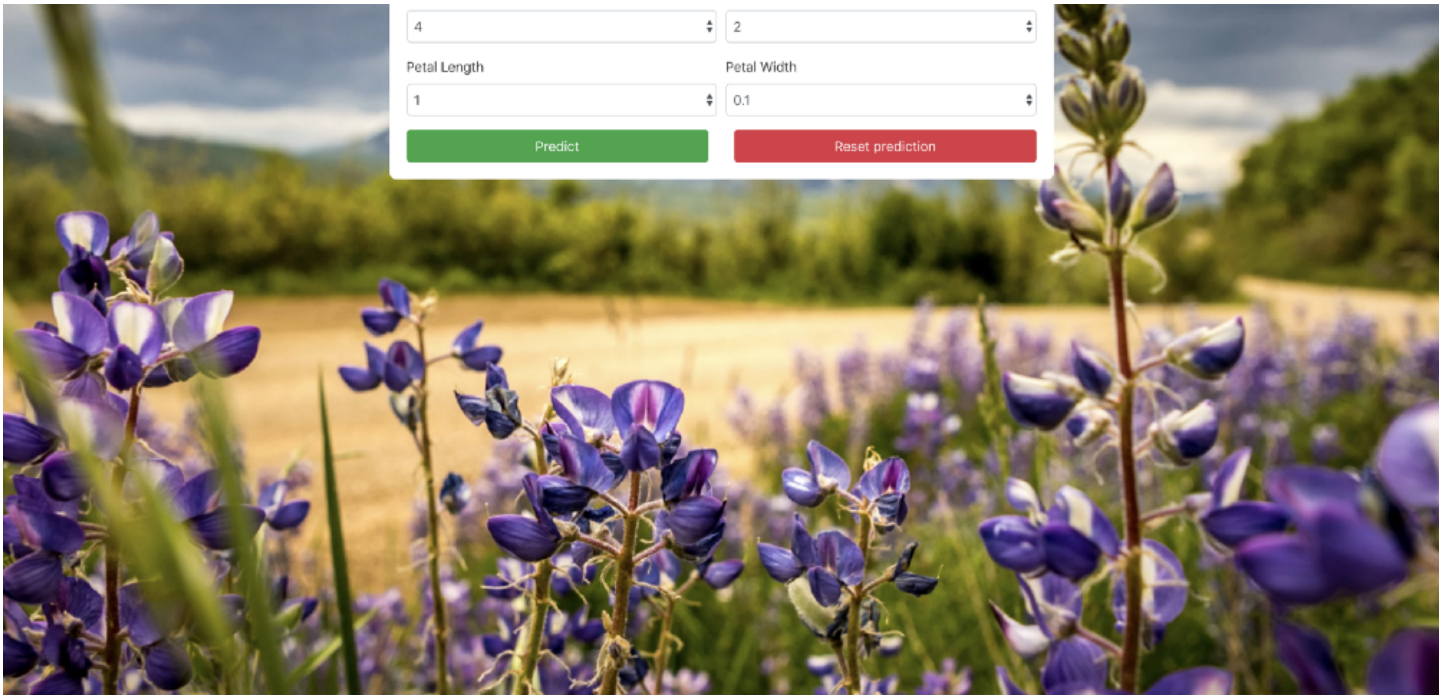
Add a new background image and title

Inside app.css, change the link of the background image to your own. I added an image of flowers from Unsplash. I also updated the title to `Iris Plant Classifier` and the page title too inside `index.html` file in the `public` folder.

Result

The application is now ready to use the model. Restart both services after building the UI using `npm run build`. The application looks like below:





Main Page

With some feature values, on pressing the `Predict` button, the model classifies it as `Iris Setosa`.

With new feature values, the model predicts the plant to be `Iris Versicolour`.

Conclusion

As you can see, in this article, I discussed a ML React App template that will make creating complete ML applications simple and quick.

. . .

Try the application for your own use case and share your feedback. I'd love to hear from you.

Python React Technology Development Machine Learning

Medium About Help Legal