MLOps: Deploying Models

Ed Shee - Seldon

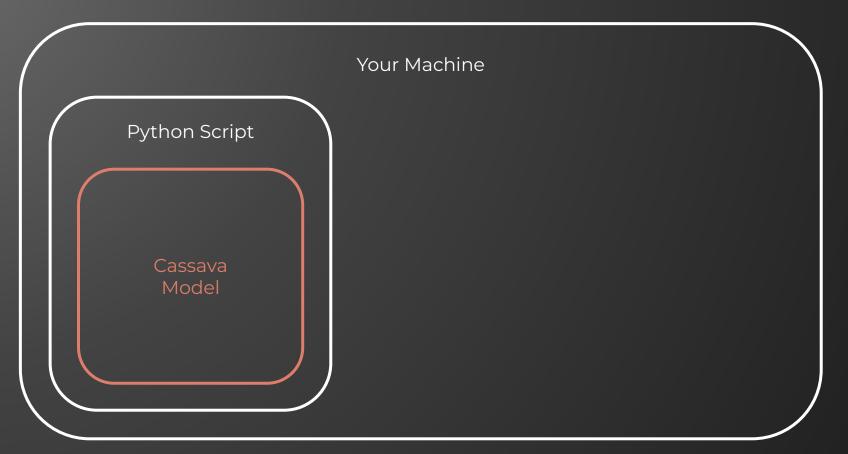
What we'll cover

- How to turn your model into an API
- Containerize your model
- Store your container in a registry
- Deploy your model to a cloud compute cluster
- Scale up your model



The ML Model







The model can't be accessed outside of the python process...



```
import numpy as np
from flask import Flask, request
import pickle
model = pickle.load(open('model.pkl', 'rb'))
@app.route('/predict', methods=['POST'])
def predict():
  int_features = [int(x) for x in request.form.values()]
  final_features = [np.array(int_features)]
  prediction = model.predict(final features)
 output = round(prediction[0], 2)
  return output
if name = " main ":
 app.run(debug=True)
```

Why not use Flask or FastAPI?



Production deployment challenges

- Maximizing infrastructure usage
- Dependency management
- Working with multiple ML frameworks

- Standardizing API definitions
- Capturing payload structures
- Handling multiple versions of models
- Collecting metrics







MLServer

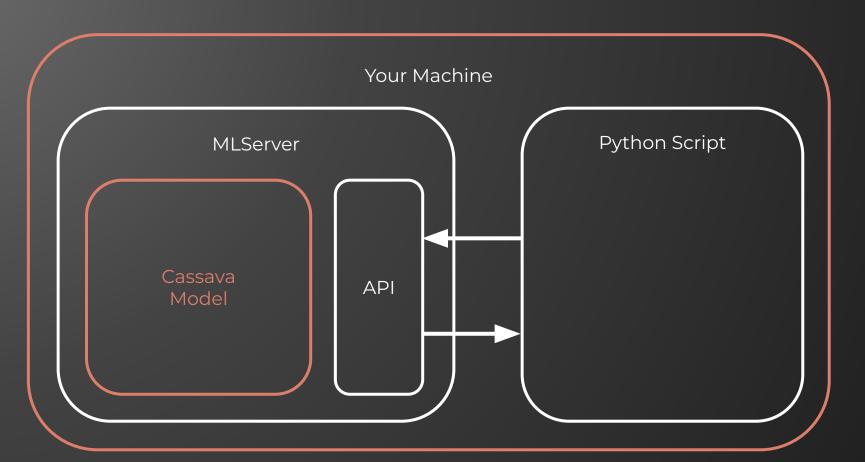
- An Open Source inference server for machine learning models
- Serves models over standardised REST and gRPC interfaces
- Supports popular python based ML frameworks





Turning your model into an API







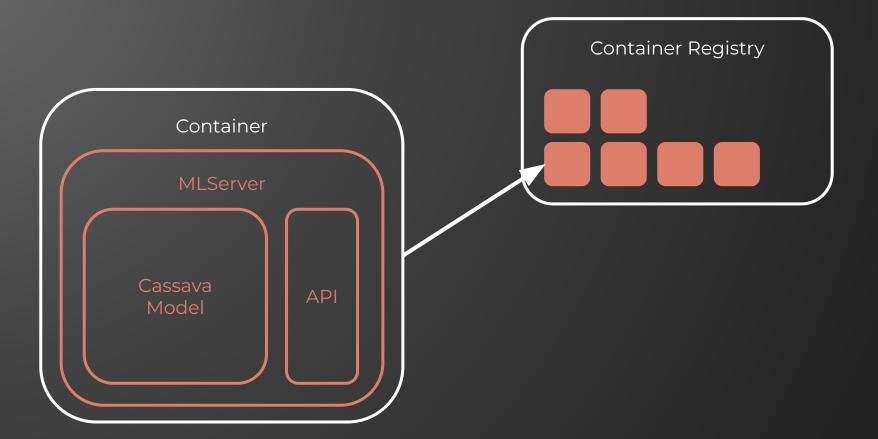
Your model is useless on your machine...





Packaging your model as a container

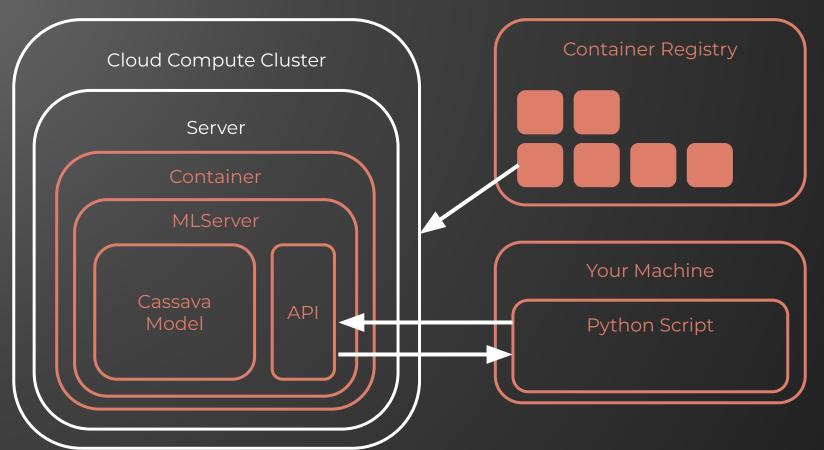






Deploying your model to the cloud



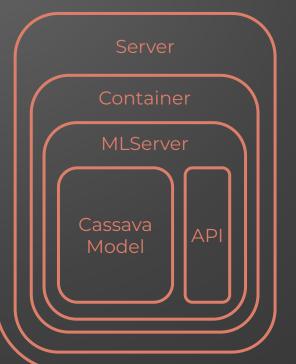


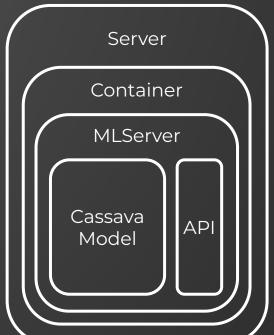


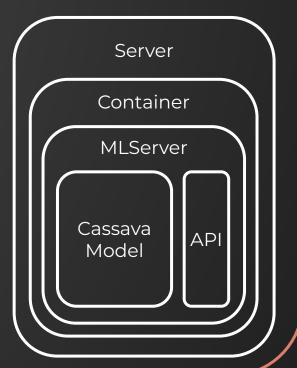
Scaling your model



Cloud Compute Cluster









Conclusion

- Your model is useless on your machine
- Creating an API makes your model accessible
- Containerization is an easy way to package models.
- Deploying to cloud keeps your API running
- Scaling helps you avoid downtime



Thank You

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