Getting Your Model in Production

Making your code useful, and common pitfalls to avoid

What is "Production"

Production *is an environment which users (internal or external) will interact with*

We want this software to be *stable* and *bug-free*

DTAP: Keeping Production Bug-Free

- Development: Where code is developed (eg. laptop, cluster, etc)
- Testing: Where code is tested against a set of tests, including test data
- Acceptance: Shadow-copy of production. Test integration with other acceptance environments
- Production: Where the code is actually used

TLDR: Moving D -> P means more data, and more security.

Normal IT vs Data Science

DTAP was created for *traditional* software development, Data-Science is a little different.

- We need real data to develop models
- Writing unit-tests for a model isn't trivial

Not All P is the Same

At ING we categorize **Production** according to 3 things:

- Confidentiality: How bad is it if this data leaks out?
- Integrity: How bad is it if the data is incorrect?
- Availability: How bad is it if this service can't be reached?

Together these are called the CIA rating

The higher the CIA rating is, the stricter the requirements are

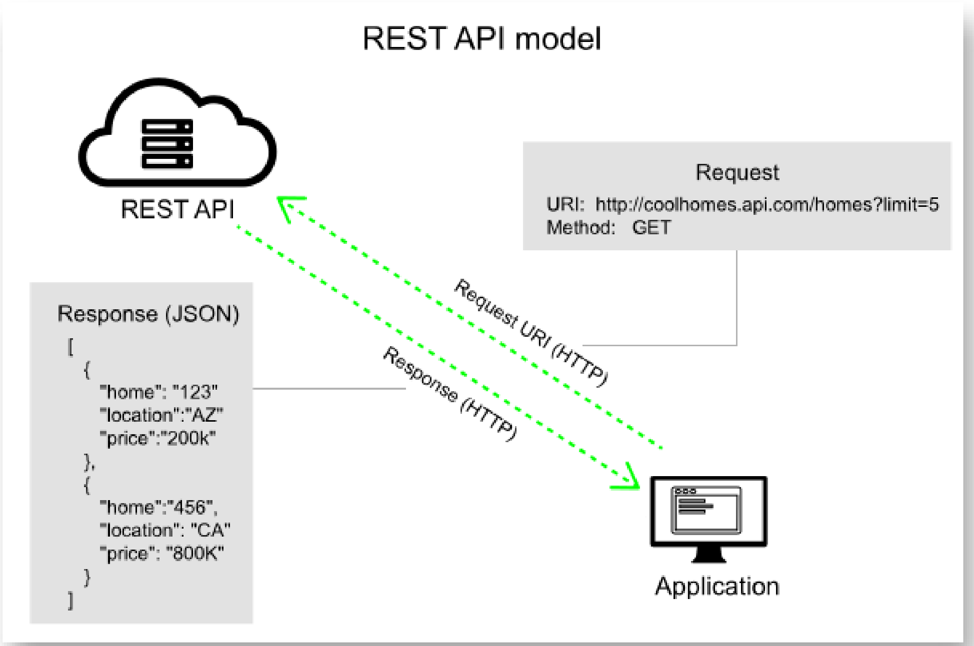
Putting DS Models into Production

After we develop our fancy statistical models, we want them to be used.

How?

- Scheduled batch processing
- On-demand API

Serving Models as a (REST) API



1. An application sends an HTTP request (**model features**)
2. The server returns a response (**the prediction**)

Flask (easy API's in python)

Flask is a **web-framework** in python

Hello world:

```python
from flask import Flask
app = Flask(__name__)

@app.route('/')
def hello_world():
    return 'Hello, World!'

if __name__ == '__main__':
    app.run()
```

1. Easy to setup an API with a few lines of code
2. Integrates nicely with existing DS tools, since Flask is python

Example of Model API

```python
# Here we specify the endpoint ('http://mywebsite.com/api') and specify GET requests
@app.route('/api', methods=['GET'])
def make_prediction():

    # Here we retrieve the features from the API request
    features = request.args.get('features')

    # If we already loaded our trained classifier, we do our prediction
    pred = clf.predict(features)

    # We return our prediction in JSON
    return jsonify({"pred": pred})
```

Python's pickle

Standard to save/load python objects as files

```python
# Here we write our object to a file
with open('my_pickle.pkl', 'wb') as file:
    pickle.dump(my_object, file)

# In some other script or environment we load the same object
with open('my_pickle.pkl', 'rb') as file:
    same_object = pickle.load(file)
```

Can be loaded with `import pickle`, and is included with python

Great for saving a trained scikit-learn pipeline!

Production Code

Informative

- Logging what it does
- Easy to debug after its run (we can trace each step)

Robust

- Expect the unexpected (weird input values, restarts)
- Fail graciously, restart

Bug-free

- Simple code is easier to keep bug-free, and to test

Logging

Most software uses logfiles, which are central files which contain **one-liners** with useful information

```
Jul  4 09:09:38 XPS13 kernel: [34472.952336] IPv6: ADDRCONF(NETDEV_UP): wlp58s0: link is not ready
Jul  4 09:09:38 XPS13 kernel: [34473.032310] IPv6: ADDRCONF(NETDEV_UP): wlp58s0: link is not ready
Jul  4 09:09:43 XPS13 kernel: [34477.930333] wlp58s0: authenticate with c4:0a:cb:89:fa:ed
Jul  4 09:09:43 XPS13 kernel: [34477.980418] wlp58s0: send auth to c4:0a:cb:89:fa:ed (try 1/3)
Jul  4 09:09:43 XPS13 kernel: [34477.981070] wlp58s0: authenticated
Jul  4 09:09:43 XPS13 kernel: [34477.983282] wlp58s0: associate with c4:0a:cb:89:fa:ed (try 1/3)
Jul  4 09:09:43 XPS13 kernel: [34477.988447] wlp58s0: RX AssocResp from c4:0a:cb:89:fa:ed (capab=0x101 status=0 aid=1
Jul  4 09:09:43 XPS13 kernel: [34477.991089] wlp58s0: associated
Jul  4 09:09:43 XPS13 kernel: [34477.991342] ath: EEPROM regdomain: 0x8210
Jul  4 09:09:43 XPS13 kernel: [34477.991344] ath: EEPROM indicates we should expect a country code
Jul  4 09:09:43 XPS13 kernel: [34477.991346] ath: doing EEPROM country->regdmn map search
Jul  4 09:09:43 XPS13 kernel: [34477.991349] ath: country maps to regdmn code: 0x37
Jul  4 09:09:43 XPS13 kernel: [34477.991351] ath: Country alpha2 being used: NL
Jul  4 09:09:43 XPS13 kernel: [34477.991352] ath: Regpair used: 0x37
Jul  4 09:09:43 XPS13 kernel: [34477.991355] ath: regdomain 0x8210 dynamically updated by country IE
Jul  4 09:09:43 XPS13 kernel: [34477.991991] IPv6: ADDRCONF(NETDEV_CHANGE): wlp58s0: link becomes ready
```

Logging in Python

Python has a built-in module for logging, `import logging`.

```
import logging

logger = logging.getLogger()
handler = logging.StreamHandler()
formatter = logging.Formatter('%(asctime)s %(name)-12s %(levelname)-8s %(message)s')
handler.setFormatter(formatter)
logger.addHandler(handler)
logger.setLevel(logging.DEBUG)

logger.debug('Something just happened, I'd better send it to the debugger!')
```

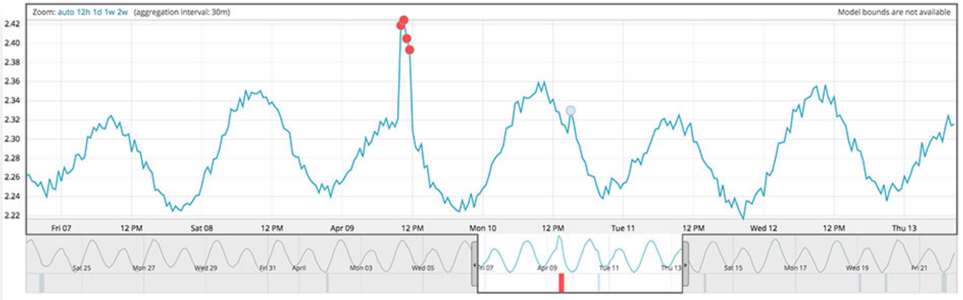
What to Log

The rule of thumb with logging, log anything which can help you debug in the future:

1. Loading of objects
2. Preprocessing of data (which can fail)
3. When a request happens
4. Who made the request
5. Writing of information to databases

Ask your friendly DevOps for advice, they're much better at this stuff

Model Monitoring

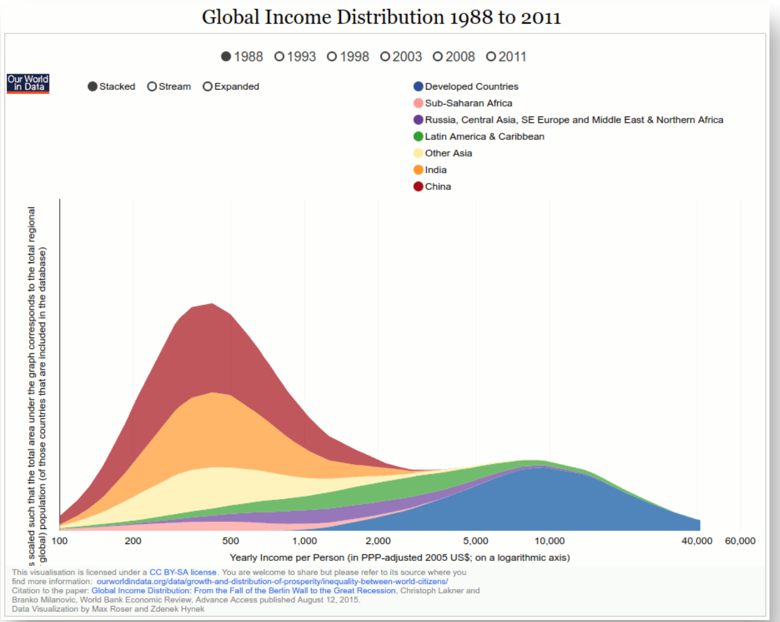


We look at this dashboard or report when we have problems like:

- What is the current accuracy of my model?
- Why is the accuracy going down?
- Has the distribution of my population changed?

So is my model working as expected, and if not, why?

What Causes Model Degradation?



Lots of possible causes:

1. Data is gathered in a different way
2. The population you are scoring on has a different distribution than in training
3. The nature of the problem has changed

What to Look At

In general you should monitor:

- DS metrics like AUC/precision/recall, but also business relevant metrics
- Follow your feature distributions over time, to understand why your performance is changing
    - Compare them with the training distributions
- Anything else that might be useful

Robust Code

Use `try/catch` when you think code might fail:

```
try:
    # This code might fail
    output = func(input)

# This block is executed when it does with a SpecificError
except SpecificError as e:
    # We log this error, to help us in the future
    logger.log("[ERROR] {error}".format(error = e))
    # We might need to clean up if the error happens
    on_fail_do()
    clean_up()
```

Bug-free Code

Unit-tests can help prevent bugs

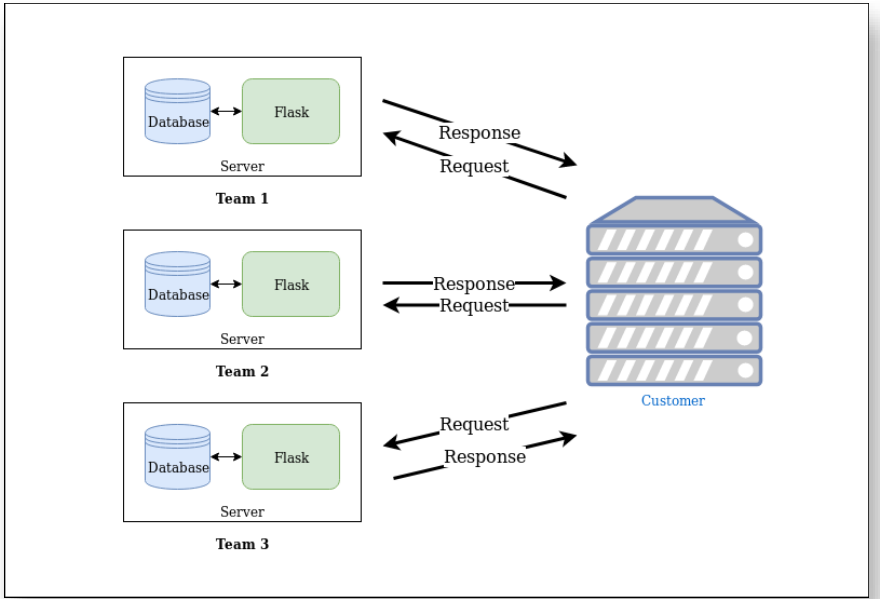
```python
import unittest

def fun(x):
    return x + 1

class MyTest(unittest.TestCase):
    def test(self):
        self.assertEqual(fun(3), 4)
```

For more information on unittesting and python testing frameworks, look at pytest

Other Issues to Keep in Mind

- Oops, I used information in Dev that wasn't available in Prod
- My score influences the outcome (example collections, fraud)
- Can take a while before you get feedback on the true label/score

Mini-Game: Building your own API



1. You're going to train a model and serve it as an API in flask
2. A "customer" will be requesting model predictions from your API
   - If you predict the correct outcome, you get 1 points
   - If you return a prediction successfully, you get 0 points
   - If you fail to return a prediction, you get -1 points

How to Play

What you get

1. Server with a database already setup
2. A training dataset
3. Some starter code

What you need to do

1. Train a model
2. Get your API working in flask
3. Save your results to a database to retrain your model in the future
4. Whatever you think will help you get the top score!

Starter Project

```
.
├── data                            # Put data here
│   └── train_data.csv              # Initial training data
├── database_docker
├── main.py                         # Flask code
├── models                          # Save your trained models here
├── modules
│   └── database.py                 # Some useful functions for working with the database
├── notebooks
│   └── training_notebook.ipynb     # This can be used to train your model
├── output                          # Save any reports here
└── server
```

Instructions

- Creating users
- How to connect (SSH)
- How to work with database