BRENTON MALLEN

MACHINE LEARNING AS A MICROSERVICE

BIO

Masters in Ocean Engineering

Underwater mine detection and classification using sonar image processing

Data Scientist in Cyber Security

Performing R&D, ad hoc analyses and building production ML systems for internet bot detection and mitigation

INTENT

Illustrate an approach to a product development cycle of getting data, building a machine learning model and turning it into something that can be used by others.



AGENDA

Problem Background

Build a Machine Learning Model

Build a Web App/API (Microservice)

Demo

Code Snippets along the way!

Source Code: https://github.com/brentonmallen1/titanic_survival

LANGUAGES & TECH

Python

sklearn, pandas, flask, zappa

HTML

Javascript

Amazon Web Services (AWS)

Lambda, API Gateway

THE PROBLEM BACKGROUND

THE TITANIC PROBLEM

Objective:

Predict if a passenger would have survived the titanic



https://www.kaggle.com/c/titanic

THE DATA

Training Set

891 records

Label: Survival

Test Set

418 records

Data Variables
Survival
Ticket class
Sex
Age in years
of siblings / spouses aboard
of parents / children aboard
Ticket number
Passenger fare
Cabin number
Port of Embarkation

BUILD A MODEL

What does every ML model need?



CHOOSING & ENGINEERING FEATURES

Removed ship location related features

Not particularly useful without knowledge of the ship layout

New features:

Age and Fare groups

Is Alone

Data Variables Ticket class Sex Age in years # of siblings / spouses aboard # of parents / children aboard Ticket number Passenger fare Cabin number Port of Embarkation

FEATURE CHALLENGES

Small Set

891 Train Records

418 Test Records

Categorical Data

Missing Data

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2833	C85	С
3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

MISSING DATA

Selecting Most Common

```
most_common_embark = df['Embarked'].mode()[0]
df['Embarked'] = df['Embarked'].fillna(most_common_embark)
```

Selecting Median Value

```
test_data['Fare'] = test_data['Fare'].fillna(test_data['Fare'].median())
test_data['Fare'] = test_data['Fare'].apply(fare_groups)
```

MISSING DATA

Predict Using a Classifier*

```
# Fill missing ages and encode them into age groups
age features = [f for f in utils.FEATURES if f != 'Age']
age clf = utils.missing clf(train data,
                                  age features,
                                  'Age'
train data['Age'] = (train data.
     apply(
     lambda x: utils.predict encode age(
         features=age features,
         clf=age clf
     axis=1
def predict encode age (row: pd.Series,
                   features: List = [],
                   clf: RandomForestClassifier = None) -> int:
   if pd.isnull(row['Age']):
      return age groups(clf.predict(row[features].values.reshape(1, -1))[0])
      return age groups(row['Age'])
```

```
def missing clf(df: pd.DataFrame, features: List,
                label: str) -> RandomForestClassifier:
    This function will train a classifier
   on the data with missing values. This
    classifier is can be used to fill in
   missing data.
    :param df:
    :param features:
    :param label:
   train data = df[~df[label].isna()]
   label = train data[label].astype(int) # train on
   clf = RandomForestClassifier(n estimators=250,
                                 max depth=3,
                                 bootstrap=False,
                                 oob score=False
   clf.fit(train data[features], label)
    return clf
```

*Using the output of a classifier as features for another classifier can lead to latent interactions and increased tuning complexity

ENCODING CATEGORICAL FEATURES

Sex Encoding

```
SEX_MAPPING = {'female': 0, 'male': 1}
# encode the sex data
train_data['Sex'] = train_data['Sex'].map(_utils.SEX_MAPPING)
```

Embarked Encoding

```
encoding = {f: i for i, f in enumerate(df['Embarked'].unique())}
df['Embarked'] = df['Embarked'].map(encoding)
```

ENGINEERED FEATURES

Fare Encoding

Age Encoding

```
def fare groups(fare: float):
    a defined interval
    :param fare:
    if fare < 7.78:</pre>
        return 0
    elif 7.78 <= fare < 8.66:
        return 1
    elif 8.66 <= fare < 14.45:
        return 2
    elif 14.45 <= fare < 26.0:
        return 3
    elif 26.0 <= fare < 52.37:
        return 4
    elif 52.37 <= fare < 512.33:
        return 5
    else:
        return 6
```

```
def age groups(age):
    77 77 77
    This function creates age groups
    if age < 10:
        return 0
    elif 10 <= age < 18:
        return 1
    elif 18 <= age < 26:
        return 2
    elif 26 <= age < 36:
        return 3
    elif 36 <= age < 48:
        return 4
    elif 48 <= age < 56:
        return 5
    else:
        return 6
```

ENGINEERED FEATURES

Is Alone

```
def is_alone(row: pd.Series):
    """

This function is used to determine if a passenger was not traveling with
    anyone else
    :param row: row of titanic data
    :return: binary output of whether and passenger was traveling alone
    """

family_size = row['SibSp'] + row['Parch']
    if family_size == 0:
        return 1
    else:
        return 0
```

If the passenger has no spouse, sibling, parent or child

FINAL FEATURE SET

Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Alone
3	1	2	1	0	0	0	1
1	0	4	1	0	5	1	1
3	0	3	0	0	1	0	0
1	0	3	1	0	5	0	1
3	1	3	0	0	1	0	0

TRAIN A MODEL

An attempt to mitigate overfitting due to small sample size

MODEL INSPECTION

Cross Validation

Accuracy* (95% CI): 0.823 (+/- 0.076)

^{*}This is classification accuracy, which is the performance metric used for the Kaggle competition

MODEL INSPECTION



Women and Children First by: Fortunino Matania

Feature Importance

Feature	Importance
Sex	0.51589
Ticket Class	0.15865
Fare	0.11274
Age	0.09403
# of siblings / spouses aboard	0.04831
Embarked	0.03169
# of parents / children aboard	0.02158
Alone	0.01799

MODEL PERFORMANCE

```
# Embarked fill and encoding
                                         test data = raw test.copy() # retain original since changes are in place
                                         fill encode embark(test data)
Gather Features
                                         test data['Sex'] = test data['Sex'].map(sex mapping)
  on Test Data
                                         test data['Age'] = test data.apply(
                                            lambda x: predict encode age(x,
                                                                         features=age features,
                                                                         clf=age clf
                                         test data['Fare'] = test data['Fare'].fillna(test data['Fare'].median())
                                         test data['Fare'] = test data['Fare'].apply(fare groups)
Predict Survival
                                         test_data['Alone'] = test_data.apply(is_alone, axis=1)
                                         test data['Survived'] = survival clf.predict(test data[CLASS FEATURES])
  on Test Data
```

Test Accuracy: 0.78947*

^{*}Baseline classifier (sex as label) score: 0.76555

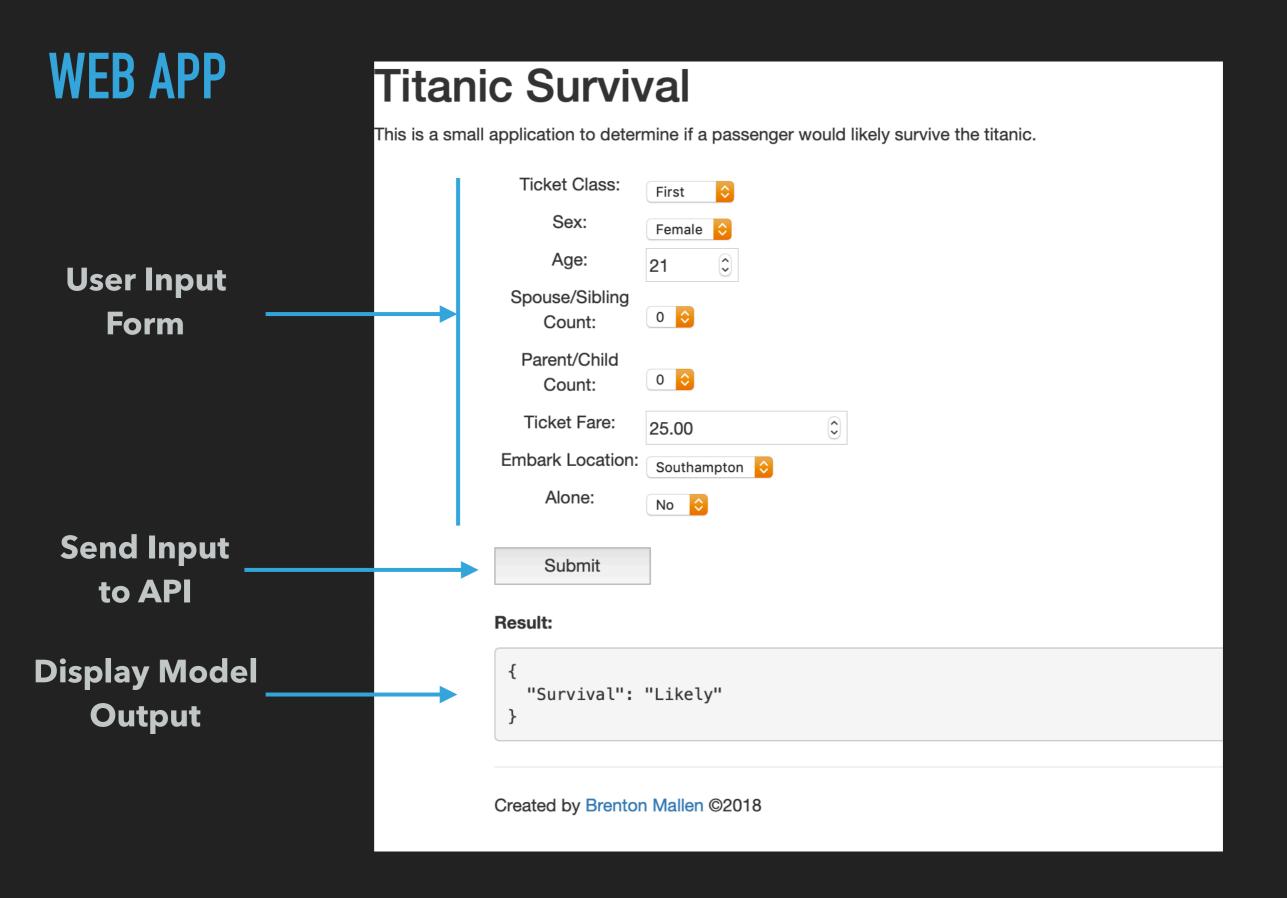
BUILD A WEB APP / API SERVICE

API

Flask App

```
@app.route('/', methods=['GET'])
                     def index(name=None):
                         :return:
Resource
                                                                                                   Method
                         return render template('titanic.html', name=name)
                     @app.route('/titanic', methods=['POST'])
                     def predict survival() -> Response:
                         clf = utils.load_model(_utils.MODEL_LOC,
                                                 utils.MODEL_NAME
                                                                                             Return Prediction
                         prediction = clf.predict(get features())[0]
                         return Response (
                             format prediction(prediction), 
                             200
```

```
<html lang="en">
                         <head>
   WEB APP
                             <meta charset="UTF-8">
                             <script src="https://ajax.googleapis.com/ajax/libs/jquery/3.3.1/jquery.min.js"></script>
                             <script src="static/js/script.js"></script>
                             <link rel="stylesheet"</pre>
                                  href="https://maxcdn.bootstrapcdn.com/bootstrap/3.3.7/css/bootstrap.min.css">
                             <title>Titanic Survival</title>
                         </head>
  Javascript
                         <body>
                         <h1>Titanic Survival</h1>
                         This is a small application to determine if a passenger would likely survive
                         the titanic.
                         <br>
                         <br>
                         <div class="container">
Form & Action
                          <form action="/dev/titanic" method="POST" enctype="multipart/form-data">
                                Ticket Class:
  User Input
                                           <select name="Pclass">
                                               <option value="1">First
                                               <option value="2">Second</option>
                                              <option value="3">Third</option>
                                           </select>
     Result
                                       <br>>
                                 <input id="submit" type="submit" name="submit"</pre>
                                       style="height:30px;width:125px"/>
                                 \langle br \rangle
                                 <br>>
                                 <strong>Result:</strong>
                                 </form>
```



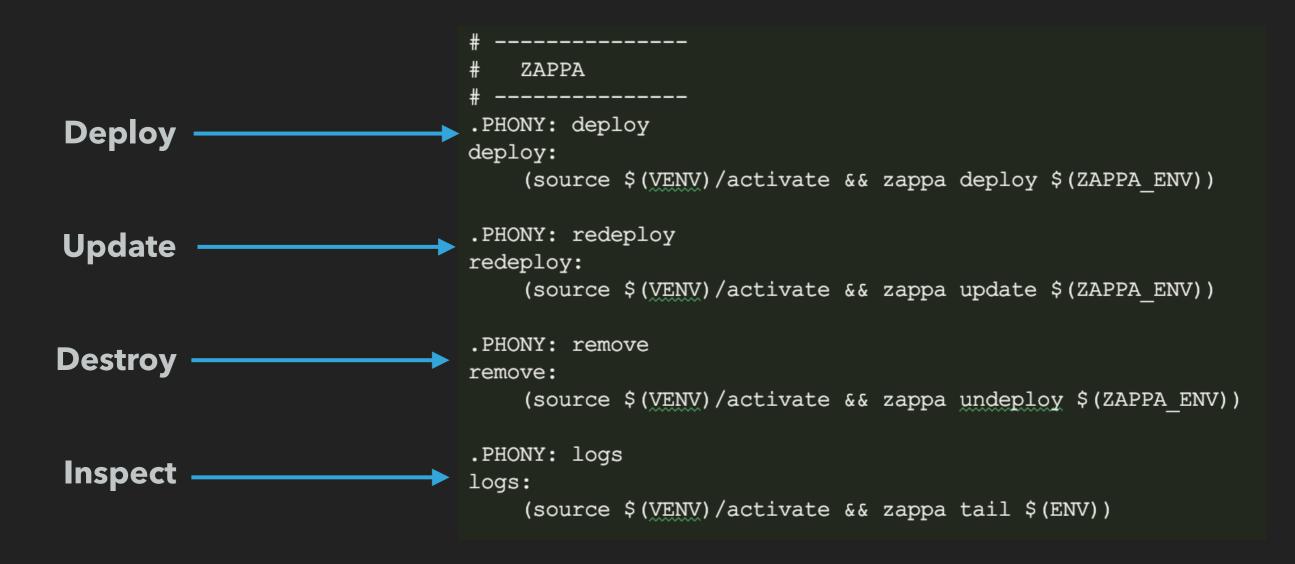
WEB APP

JavaScript

```
$ (function() {
Link to Submit
                            $ ('input[type="submit"]').click(function(event) {
                                 var $form = $(this).parent();
     Button
                                 $form.find('.output').text("")
                                 $.ajax({
                                     url: $form.attr('action'),
  Take Form
                                     data: $form.serialize(),
                                     type: 'POST',
     Input
                                     success: function(response) {
                                         $form.find('.output').text(JSON.stringify(JSON.parse(response), null, 2))
                                         console.log(response);
 Make AJAX
                                     error: function(error) {
  Call to API
                                         $form.find('.output').text(error.responseText)
                                         console.log(error);
                                 });
Return Result
                                 event.preventDefault()
                             });
   (or Error)
```

DEPLOYMENT

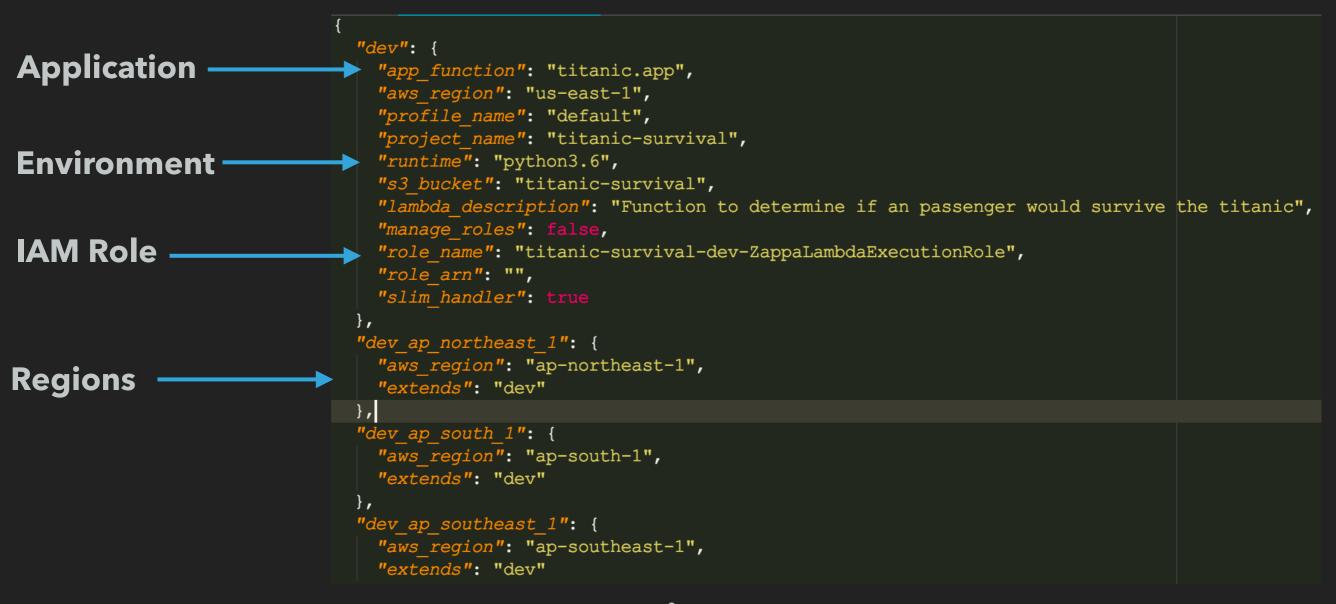
Zappa Commands*



^{*} Commands shown have been compiled into a Makefile for convenience

DEPLOYMENT

Zappa config*



[•]

^{*} Zappa requires an AWS account as well as an IAM role and policy

DEMO TIME

PRODUCTION NEXT STEPS

Continuous Integration / Deployment

AWS CodePipeline/CodeBuild, Jenkins, etc.

Monitoring / Dashboards

AWS Cloudwatch, DataDog, etc.

POSSIBLE TWEAKS

Classifier Model

Perform grid search on hyper-parameters

Try a different model or feature set

App / API

Improve app styling using CSS

Add DNS to make it more approachable

Add caching for performance

ANOTHER APPLICATION

Using this methodology we can make other apps as well

http://www.bg-similarity.com

QUESTIONS?

