

# Detecting Money Laundering FP with AI

## Building Machine Learning Recipes to Detect Malicious Behaviours

Ashrith Barthur

H<sub>2</sub>O.ai

September 17, 2019

# Contents

Overview

Anti Money Laundering

Recipe

Feature Recipe Structure

Questions

# Thanks

1. Audience
2. Our Customers
3. AI4 Team
4. H2O Team
5. Patrick Hall - Thanks for the beamer template.

## Speaker

1. Principal Security Scientist at H2O.AI.
2. Researcher in the area of anomalies specific to malicious behaviour, graduated with a PhD from Purdue.
3. Areas - Cybersecurity, Electronic Fraud, Money Laundering, and Global Malicious Migratory Patterns.
4. When I am not working, I am usually biking, or taking pictures.
5. @ashrith (github) @cyberbaggage (twitter) @ba(h2o.ai)

## Question

How many of us attending today's webinar analyse data and build models?

# Overview

This presentation introduces us to three topics. These topics are:

1. An introduction to Detecting False Positive in Money Laundering Alerts using feature recipes.
2. A simple, starter guide to building your own feature recipes.
3. A 'peek' introduction to detecting malicious behaviours. Malicious Domains in cybersecurity.

## Question

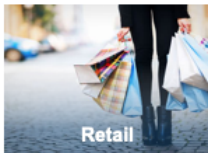
How many of the people attending today have known about H2O.AI?

# H2O.AI Overview

<b>Company</b>	Founded in Silicon Valley in 2012 Funded: \$147M Investors: Goldman Sachs, Paxion Ventures, Ping An, Nexus Ventures, NVIDIA, Wells Fargo.
<b>Products</b>	<ul style="list-style-type: none"><li>• H2O Open Source Machine Learning (18,000 organizations)</li><li>• H2O Driverless AI – Automatic Machine Learning</li></ul>
<b>Team</b>	175 AI experts (Expert data scientists, Kaggle Grandmasters, Distributed Computing, Visualization)
<b>Global</b>	Mountain View, NYC, London, Prague, India



# Industry Footprint

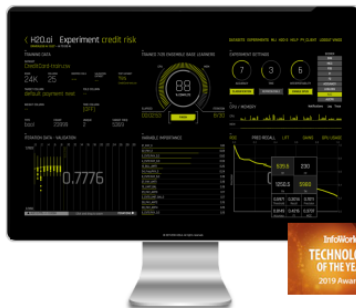


## Question

How many of the people attending today have known, or used Driverless AI?

# Driverless AI

## H2O Driverless AI: Automatic Machine Learning



21 day free trial for [Driverless AI](#)

Automatic AI and ML  
in a single platform

AI to do AI

Delivers insights  
and interpretability

Provides easy to  
understand results  
and visualizations



# Anti Money Laundering

What is money laundering?

*"the concealment of the origins of illegally obtained money, typically by means of transfers involving foreign banks or legitimate businesses."*



## Anti Money Laundering

How are we solving Anti Money Laundering up until now?

1. We use Rule-Based systems that detect instances of money laundering.

Then what remains to be a problem?

1. The Rule-Based systems are slow to evolve.
2. Rule gaps, and complexities exist.
3. They have a high false positive rate - 75% to 99%



# Anti Money Laundering

In this presentation we reduce the false positive rate of Anti Money Laundering alerts.  
How do we do this?

1. We show case a pre-built recipe for AML.
2. The feature recipe, comprehensively covers many different features that are potentially applicable for Anti-Money Laundering.
3. Through the feature recipe, we use the strengths of Driverless AI to build us the best model possible.



# DEMO

## Question

How many of us are familiar with Custom Transformers in Driverless AI?





## How Did We Build This?

Driverless AI provides an extension.

This is a class 'CustomTransformer'

```
class ExampleLogTransformer(CustomTransformer):
```



## How Did We Build This?

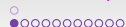
The class has:

1. Parameters that need to be provided.
2. These parameters are specific to the type of feature recipe that you are building.
3. It also has four methods which primary handle your feature engineering transformation.



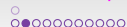
## Parameters - Basic

```
class ExampleLogTransformer(CustomTransformer):  
    _regression = True  
    _binary = True  
    _multiclass = True
```



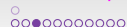
## Parameters - Advanced

```
class ExampleLogTransformer(CustomTransformer):  
    _regression = True  
    _binary = True  
    _multiclass = True  
    _numeric_output = True  
    _is_reproducible = True  
    _excluded_model_classes = ['tensorflow']  
    _modules_needed_by_name = ["custom_package==1.0.0"]
```



## Acceptance Method

```
class ExampleLogTransformer(CustomTransformer):  
    _regression = True  
    _binary = True  
    _multiclass = True  
    _numeric_output = True  
    _is_reproducible = True  
    _excluded_model_classes = ['tensorflow']  
    _modules_needed_by_name = ["custom_package==1.0.0"]  
  
    @staticmethod  
    def do_acceptance_test():  
        return True
```



## Input Data

```
...  
@staticmethod  
def do_acceptance_test():  
    return True  
  
@staticmethod  
def get_default_properties():  
    return dict(col_type = "numeric", min_cols = 1, max_cols = 1,  
                relative_importance = 1)
```



## Input Data Types

- a. "all" - all column types
- b. "any" - any column types
- c. "numeric" - numeric int/float column
- d. "categorical" - string/int/float column considered a categorical for feature engineering
- e. "numcat" - allow both numeric or categorical
- f. "datetime" - string or int column with raw datetime such as '%Y/%m/%d %H:%M:%S' or '%Y%m%d%H%M'



## Input Data Types

- g. "date" - string or int column with raw date such as  
'%Y/%m/%d' or '%Y%m%d'
- h. "text" - string column containing text  
(and hence not treated as categorical)
- i. "time\_column" - the time column specified at the start of  
the experiment (unmodified)





## Fit Function

```
@staticmethod
def get_default_properties():
    return dict(col_type = "numeric", min_cols = 1, max_cols = 1,
                relative_importance = 1)

def fit_transform(self, X: dt.Frame, y: np.array = None):
    X_pandas = X.to_pandas()
    X_p_log = np.log10(X_pandas)
    return X_p_log
```



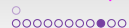
## Transform Function

```
def fit_transform(self, X: dt.Frame, y: np.array = None):  
    X_pandas = X.to_pandas()  
    X_p_log = np.log10(X_pandas)  
    return X_p_log
```

```
def transform(self, X: dt.Frame):  
    X_pandas = X.to_pandas()  
    X_p_log = np.log10(X_pandas)  
    return X_p_log
```

## Machine Generated Domains Detection - Recipe

In this presentation we look at how a recipe built to detect machine generated domains works, and performs.



# DEMO



## Advantages

1. Feature engineering process standardised by:
  - 1.1 preset parameters
  - 1.2 preset methods
2. Effort minimisation leads to minimisation in time spent.
3. Build only once - Feature engineering is carried over from training/testing to production.
4. DAI automatically, runs multiple models on various sets of features to get the best model.
5. All the requirements are handled internally by DAI.

## References

### How to build a recipe

[https:](https://github.com/h2oai/driverlessai-recipes/tree/master/how_to_write_a_recipe)

[//github.com/h2oai/driverlessai-recipes/tree/master/how\\_to\\_write\\_a\\_recipe](https://github.com/h2oai/driverlessai-recipes/tree/master/how_to_write_a_recipe)

# Questions

Thanks