

Machine Learning Bootcamp

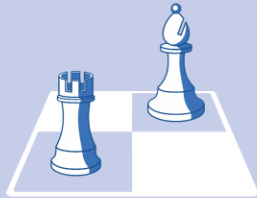
IDUG NA 2019: June 6, 2019

Mark Ryan mryan@ca.ibm.com
Jason Shayer shayer@ca.ibm.com
Steve Darling darling@ca.ibm.com
Roger Sanders roger.sanders@us.ibm.com

What is Machine Learning?

Artificial Intelligence (AI)

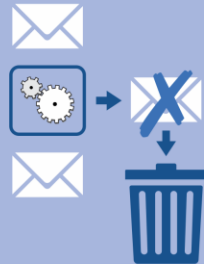
Human intelligence exhibited by machines



- Reasoning
- Natural Language Processing (NLP)
- Planning

Machine Learning (ML)

An approach to achieve AI



- Gradient Boosting Machine (GBM)
- Support Vector Machine (SVM)
- Logistic Regression
- Factorization Machines (FM)
- Field-aware Factorization Machines (FFM)

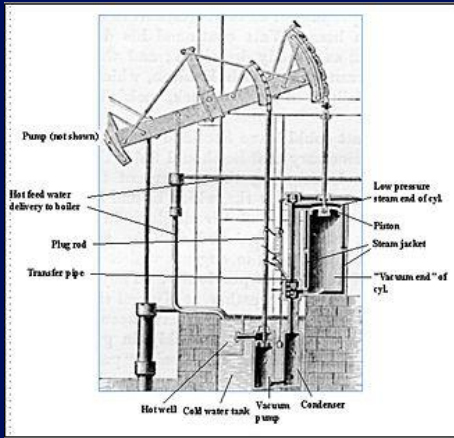
Deep Learning (DL)

A technique for implementing ML



- Deep Neural Networks
- Deep Belief Networks
- Recurrent Neural Networks

Where are we in the lifecycle of Machine Learning?



1770's:

- Watt's stationary engine
- Capital-intensive one-off applications

ML era: late 2000s



1829:

- Stephenson's Rocket
- Standardization and regular service

ML era: 2019



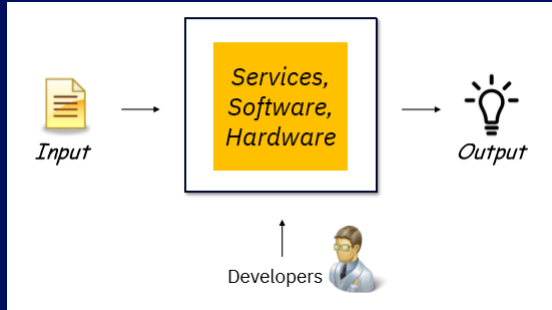
1941:

- Allegheny locomotive
- Apex of steam technology

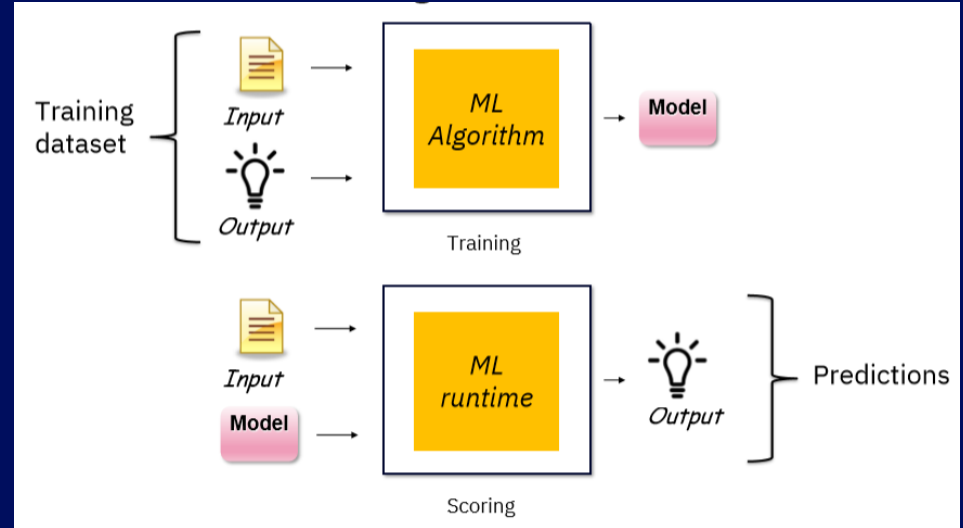
ML era: 5-10 years from now?

What is Machine Learning?

Classical Programming



Machine Learning

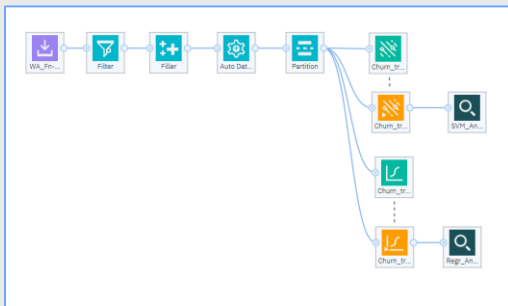


Customer churn: use case to illustrate machine learning

- **Customer churn:** when a customer ends their relationship with a business
- **PROBLEM:** You need to predict which of your customers are loyal and which are at risk of churning
- **SOLUTION:** Use data you have about clients to build a model that can predict whether a given client is going to churn



Customer Churn: the game plan



2

Solve the customer churn problem using Python

The model predicts that this client will churn

	MonthlyCharges	TotalCharges	InternetService	PaymentMethod	OnlineSecurity	Contract	tenure
0	90.5	1791.5	Fiber optic	Credit card (automatic)	No	Month-to-month	20.0

1

Solve the customer churn problem using Modeler

Python: Ingest Dataset

Click on the cell below to highlight it.

Then go to the **File** section to the right of this notebook and click **Insert** **to: code** for the data you have uploaded. Choose **Insert** **genders DataFrame**.

```
url="https://raw.githubusercontent.com/ryasmack1867/usa2019_gd_bootstrap/master/Wa_Fn-UseC_Telco-Customer-Churn.csv"
customer_data = pd.read_csv(url)
customer_data.head()
```

5(1):

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges
0	7580	Female	0	Yes	No	1	No	No phone service	DSL	No	No	No	No	No	Month-to-month	Yes	Electronic check	29.85
1	5575	Male	0	No	No	34	Yes	No	DSL	Yes	Yes	No	No	No	One year	No	Mailed check	56.95
2	3959	Female	0	No	No	2	Yes	No	DSL	Yes	No	No	No	No	Month-to-month	Yes	Mailed check	53.85
3	7795	Male	0	No	No	45	No	No phone service	DSL	Yes	Yes	Yes	No	No	One year	No	Bank transfer (automatic)	42.30
4	9237	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No	No	Month-to-month	Yes	Electronic check	70.70

5 rows x 21 columns

3

Define a pipeline in Python to predict if a client will churn

Customer churn: dataset

- CSV (comma separated values) file with ~7k records; 21 columns
- Numeric columns: **tenure**, **MonthlyCharges**, **TotalCharges**
- Categorical columns: **gender**, **SeniorCitizen**, **Partner**...
- Target / Label: **Churn**

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBack	DevicePro	TechSupp
7590-VHVEG	Female	0	Yes	No	1	No	No phone serv	DSL	No	Yes	No	No
5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No
3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No
7795-CFOCW	Male	0	No	No	45	No	No phone serv	DSL	Yes	No	Yes	Yes
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No
9305-CDSKC	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No	Yes	No
1452-KIOVK	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes	No	No
6713-OKOMC	Female	0	No	No	10	No	No phone serv	DSL	Yes	No	No	No
7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	No	No	Yes	Yes
6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes	No	No
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No	No	No

Customer churn: preparing the dataset for ML

Original dataset

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBacDeviceProTechSup		
7590-VHVEG	Female	0	Yes	No	1	No	No phone serv	DSL	No	Yes	No	No
5575-GWQDE	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No
3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No
7795-CFOCW	Male	0	No	No	45	No	No phone serv	DSL	Yes	No	Yes	Yes
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No
9305-CDSKL	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No	Yes	No
1452-MQVIR	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes	No	No
6713-QKMC	Female	0	No	No	10	No	No phone serv	DSL	Yes	No	No	No
7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	No	No	Yes	Yes
6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes	No	No
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No	No	No

Why?

Keep a subset of columns

Pick just the columns needed for the model

Deal with missing values

ML algorithms need numeric input

Deal with outliers

Control impact of anomalies

Scale continuous values

Consistent impact of columns

Deal with string values

ML algorithms need numeric input

Split Dataset into Train & Test

Need to reserve a portion of the data the model has never seen to validate the model

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBacDeviceProTechSup
7590-VHVEG	Female	0	Yes	No	1	No	No phone serv	DSL	No	Yes
5575-GWQDE	Male	0	No	No	34	Yes	No	DSL	Yes	No
3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes
7795-CFOCW	Male	0	No	No	45	No	No phone serv	DSL	Yes	No
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No
9305-CDSKL	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No
1452-MQVIR	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes
6713-QKMC	Female	0	No	No	10	No	No phone serv	DSL	Yes	No
7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	No	No
6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBacDeviceProTechSup
7590-VHVEG	Female	0	Yes	No	1	No	No phone serv	DSL	No	Yes
5575-GWQDE	Male	0	No	No	34	Yes	No	DSL	Yes	No
3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes
7795-CFOCW	Male	0	No	No	45	No	No phone serv	DSL	Yes	No
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No
9305-CDSKL	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No
1452-MQVIR	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes
6713-QKMC	Female	0	No	No	10	No	No phone serv	DSL	Yes	No
7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	No	No
6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No

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Customer churn: preparing the dataset for ML

Original dataset

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBacDevicePro	TechSup
7590-VHVEG	Female	0	Yes	No	1	No	No phone serv	DSL	No	Yes	No
5575-GWDE	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes
3668-OPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No
7795-CFCOW	Male	0	No	No	45	No	No phone serv	DSL	Yes	No	Yes
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No
9305-CDSKC	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No	Yes
1452-MQVIR	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes	No
6713-OKMNC	Female	0	No	No	10	No	No phone serv	DSL	Yes	No	No
7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	No	No	Yes
6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes	No
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No	No

Keep a subset of columns

Deal with missing values

Deal with outliers

Scale continuous values

Deal with string values

Split Dataset into Train & Test

Pick the 8 columns used for the model:

- *tenure*
- *InternetService*
- *OnlineSecurity*
- *Contract*
- *PaymentMethod*
- *MonthlyCharges*
- *TotalCharges*
- *Churn*

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBacDevicePro	TechSup
7590-VHVEG	Female	0	Yes	No	1	No	No phone serv	DSL	No	Yes	No
5575-GWDE	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes
3668-OPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No
7795-CFCOW	Male	0	No	No	45	No	No phone serv	DSL	Yes	No	Yes
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No
9305-CDSKC	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No	Yes
1452-MQVIR	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes	No
6713-OKMNC	Female	0	No	No	10	No	No phone serv	DSL	Yes	No	No
7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	No	No	Yes
6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes	No
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No	No

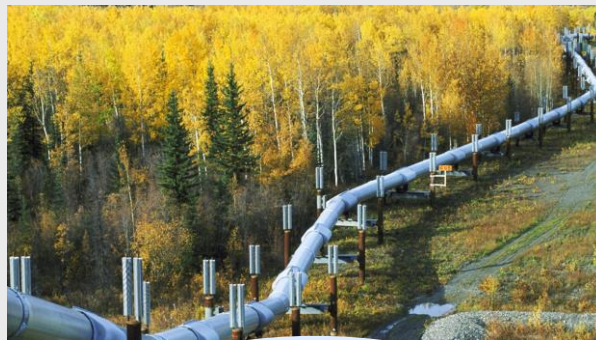
customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBacDevicePro	TechSup
7590-VHVEG	Female	0	Yes	No	1	No	No phone serv	DSL	No	Yes	No
5575-GWDE	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes
3668-OPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No
7795-CFCOW	Male	0	No	No	45	No	No phone serv	DSL	Yes	No	Yes
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No
9305-CDSKC	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No	Yes
1452-MQVIR	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes	No
6713-OKMNC	Female	0	No	No	10	No	No phone serv	DSL	Yes	No	No
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6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes	No
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No	No

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Customer churn: the pipeline

Original dataset

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBac DevicePro	TechSupp	
7590-VHVEG	Female	0	Yes	No	1	No	No phone serv	DSL	No	Yes	No	No
5575-GWVOE	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No
3668-OPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No
7795-CFOCW	Male	0	No	No	45	No	No phone serv	DSL	Yes	No	Yes	Yes
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No
9305-CDSKC	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No	Yes	No
1452-MQVVK	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes	No	No
6713-OKOMC	Female	0	No	No	10	No	No phone serv	DSL	Yes	No	No	No
7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	No	No	Yes	Yes
6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes	No	No
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No	No	No



Split Dataset into Train & Test

Keep a subset of columns

Deal with missing values

Deal with outliers

Scale continuous values

Deal with string values

Logistic Regression model

Pipeline:

- *Train the data preparation steps and the model in one operation*
- *Apply pipeline to get a churn / no churn prediction for a given client*
 - *Performs data prep on client's data*
 - *Applies model to get a prediction*

Machine learning models: Logistic Regression

- Classification: churn / no churn
- Extension of **linear regression**
 - simplest algorithm; used to predict continuous values
 - e.g. predict house price from # of bedrooms, sq. ft, frontage
- Logistic regression is “geared” to output between 0 and 1
 - treat 0.5 as the boundary



Machine learning models: Logistic Regression

- Define function: $\hat{Y} = h = \text{sigmoid}(X\theta)$
- \hat{Y} is the prediction (*predicted churn values*)
- X is the input
- θ is an array of weights

$$\text{Sigmoid}(z) = \frac{1}{1 + e^{-z}}$$

X

Y

Not quite!

MonthlyCharges	TotalCharges	InternetService	PaymentMethod	OnlineSecurity	Contract	tenure
29.85	29.85	DSL	Electronic check	No	Month-to-month	1
56.95	1889.50	DSL	Mailed check	Yes	One year	34
53.85	108.15	DSL	Mailed check	Yes	Month-to-month	2
42.30	1840.75	DSL	Bank transfer (automatic)	Yes	One year	45
70.70	151.65	Fiber optic	Electronic check	No	Month-to-month	2

Churn
No
No
Yes
No
Yes

Machine learning models: the secret sauce

- Define a **loss function** (delta between predictions $\hat{\mathbf{Y}}$ and actual values \mathbf{Y}):

$$h = g(X\theta)$$
$$J(\theta) = \frac{1}{m} \cdot (-y^T \log(h) - (1 - y)^T \log(1 - h))$$

- Repeatedly update θ (weights):
 - Calculate the *partial derivative* of the loss function with respect to the weights = $\mathbf{X}(\hat{\mathbf{Y}} - \mathbf{Y})$
 - Update the weights by subtracting the partial derivative
- What does making updates to the weights based on “the slope” of the loss function do?
- With these repeated updates to the weights, the loss function gets minimized and the accuracy of the model gets maximized**



Machine learning models: *all values must be numeric!*

X

Y

MonthlyCharges	TotalCharges	InternetService	PaymentMethod	OnlineSecurity	Contract	tenure
29.85	29.85	DSL	Electronic check	No	Month-to-month	1
56.95	1889.50	DSL	Mailed check	Yes	One year	34
53.85	108.15	DSL	Mailed check	Yes	Month-to-month	2
42.30	1840.75	DSL	Bank transfer (automatic)	Yes	One year	45
70.70	151.65	Fiber optic	Electronic check	No	Month-to-month	2

Churn
No
No
Yes
No
Yes



data preparation



MonthlyCharges	TotalCharges	InternetService	PaymentMethod	OnlineSecurity	Contract	tenure
-1.160323	-0.992611	0	2	0	0	-1.277445
-0.259629	-0.172165	0	3	2	1	0.066327
-0.362660	-0.958066	0	3	2	0	-1.236724
-0.746535	-0.193672	0	0	2	1	0.514251
0.197365	-0.938874	1	2	0	0	-1.236724

Churn
0
0
1
0
1

Machine learning models: Logistic Regression

- Define function: $\hat{Y} = h = \text{sigmoid}(X\theta)$
- \hat{Y} is the prediction (*predicted churn values*)
- X is the input
- θ is an array of weights

$$\text{Sigmoid}(z) = \frac{1}{1 + e^{-z}}$$

Yes!

X

Y

MonthlyCharges	TotalCharges	InternetService	PaymentMethod	OnlineSecurity	Contract	tenure
-1.160323	-0.992611	0	2	0	0	-1.277445
-0.259629	-0.172165	0	3	2	1	0.066327
-0.362660	-0.958066	0	3	2	0	-1.236724
-0.746535	-0.193672	0	0	2	1	0.514251
0.197365	-0.938874	1	2	0	0	-1.236724

Churn
0
0
1
0
1

Customer churn: exercising the model

- [churn_match_modeler-scoring.ipynb](#) to exercise the model in a notebook
- [full-blown Python](#) project to deploy and [exercise the model](#):

Customer Churn Predictor

Customer Details

Tenure Duration 100	Online Security No	Technical Support No
Contract Month-to-month	Dependents No	Phone Service No
Internet Service Fiber Optic	Payment Method Credit card	Online Backup No
Monthly Charges 30	Device Protection No	Paperless Billing No

Submit



Customer Churn Predictor

Results

This customer is not likely to churn
Probability that the customer will not churn: ~100.00%
Probability that the customer will churn: ~0.00%

Raw Model Output:
{"values": [{"tenure": 100, "contract": "Month-to-month", "internet_service": "Fiber Optic", "monthly_charges": 30, "online_security": "No", "dependents": "No", "payment_method": "Credit card", "device_protection": "No", "technical_support": "No", "phone_service": "No", "online_backup": "No", "paperless_billing": "No"}], "prediction": "not likely to churn", "probability": 1.0}

Go back and try other values

Customer Churn Predictor

Customer Details

Tenure Duration 60	Online Security No	Technical Support No
Contract Month-to-month	Dependents No	Phone Service No
Internet Service No	Payment Method Credit card	Online Backup No
Monthly Charges 100.00	Device Protection No	Paperless Billing No

Submit



Customer Churn Predictor

Results

This customer is likely to churn
Probability that the customer will not churn: ~0.00%
Probability that the customer will churn: ~100.00%

Raw Model Output:
{"values": [{"tenure": 60, "contract": "Month-to-month", "internet_service": "No", "monthly_charges": 100.0, "online_security": "No", "dependents": "No", "payment_method": "Credit card", "device_protection": "No", "technical_support": "No", "phone_service": "No", "online_backup": "No", "paperless_billing": "No"}], "prediction": "likely to churn", "probability": 1.0}

Go back and try other values

Machine learning: more background

- Overall:
 - Andrew Ng machine learning intro course: <https://www.coursera.org/learn/machine-learning>
 - Fast.ai deep learning course: <https://course.fast.ai/>
- Details:
 - Sklearn pipelines: <https://scikit-learn.org/stable/modules/generated/sklearn.pipeline.Pipeline.html>
 - Logistic Regression math & implementation in Python: https://ml-cheatsheet.readthedocs.io/en/latest/logistic_regression.html
 - Articles on a variety of machine learning topics: https://medium.com/@markryan_69718

