Machine Learning Bootcamp
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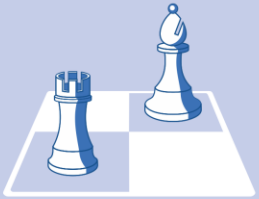
What is Machine Learning?

Artificial Intelligence (AI)

Human intelligence exhibited by machines

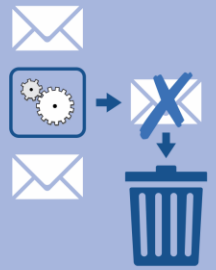
- Reasoning
- Natural Language Processing (NLP)
- Planning



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)

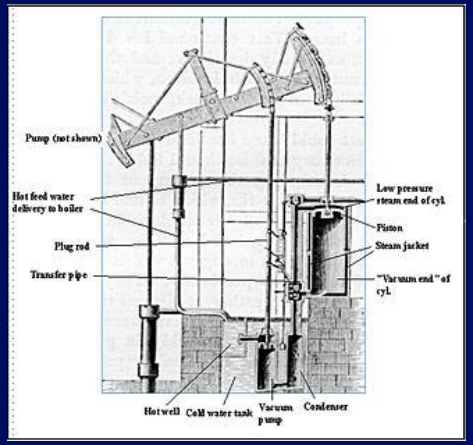


Deep Learning (DL)

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

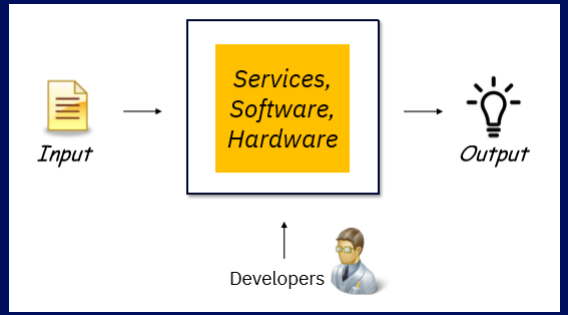
ML era: 2019

1941:
- Alleghany locomotive
- Apex of steam technology

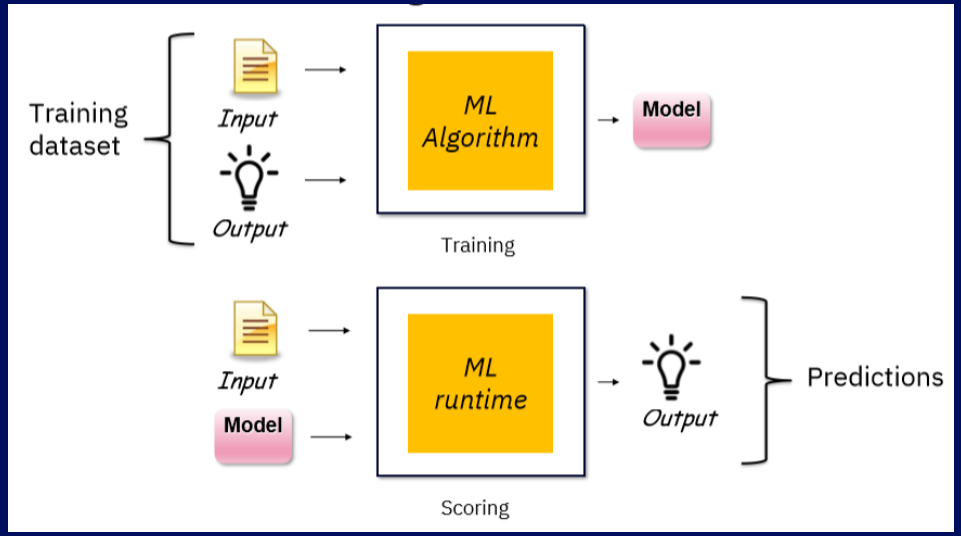
ML era: 5-10 years from now?

What is Machine Learning?

Classical Programming



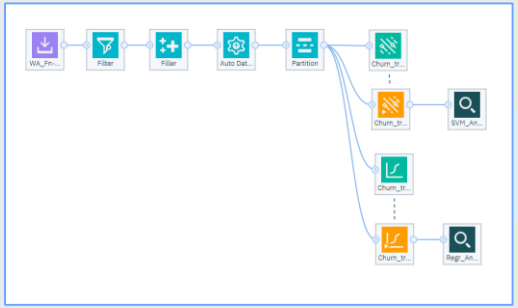
Machine Learning



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



1

Solve the customer churn problem using Modeler

2

Solve the customer churn problem using Python

Python: Ingest Dataset

Click on the cell below to highlight it.

Then go to the `Files` section to the right of this notebook and click `Insert to code` for the data you have uploaded. Choose `Insert pandas DataFrame`

```
url="https://raw.githubusercontent.com/ryanmark1867/june2019_MG_bootcamp/master/WA_Fn-UseC_-Telco-Customer-Churn.csv"
customer_data = pd.read_csv(url)
customer_data.head()
```

[6]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges
0	7590-VHVEG	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-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	No	No	No	One year	No	Mailed check	56.95
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	No	No	No	Month-to-month	Yes	Mailed check	53.85
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	No	No	No	One year	No	Bank transfer (automatic)	42.30
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	No	No	No	Month-to-month	Yes	Electronic check	70.70

5 rows × 21 columns

3

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

```
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

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	OnlineBac	DevicePro	TechSup
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	OnlineBac	DevicePro	TechSup
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

Keep a subset of columns

Deal with missing values

Deal with outliers

Scale continuous values

Deal with string values

Split Dataset into Train & Test

Why?

Pick just the columns needed for the model

ML algorithms need numeric input

Control impact of anomalies

Consistent impact of columns

ML algorithms need numeric input

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

Customer churn: preparing the dataset for ML

Original dataset

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBac	DevicePro	TechSup
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

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***

Customer churn: the pipeline

Original dataset

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBac	DevicePro	TechSup
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

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

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

Not quite!

X

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

Y

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 **Y**):

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

- Repeatedly update **θ** (weights):
  1. Calculate the *partial derivative* of the loss function with respect to the weights = $\mathbf{X}(\hat{\mathbf{Y}} - \mathbf{Y})$
  2. 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

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

Y

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

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

Yes!

X

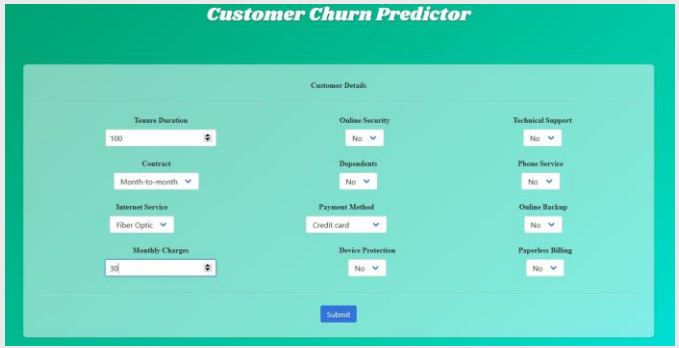
MonthlyCharges	TotalCharges	InternetService	PaymentMethod	OnlineSecurity	Contract	tenure
-1.160323	-0.992611	0	2	0	0	-1.277445
-0.259629	-0.172165	0	3	2	1	0.066327
-0.362660	-0.958066	0	3	2	0	-1.236724
-0.746535	-0.193672	0	0	2	1	0.514251
0.197365	-0.938874	1	2	0	0	-1.236724

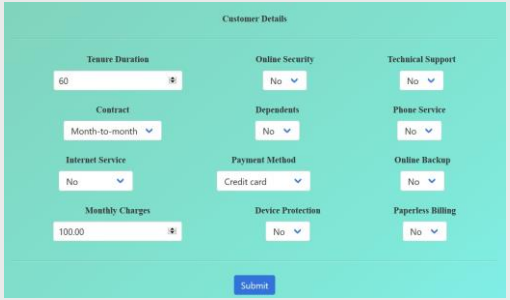
Y

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:





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