

101

Machine Learning

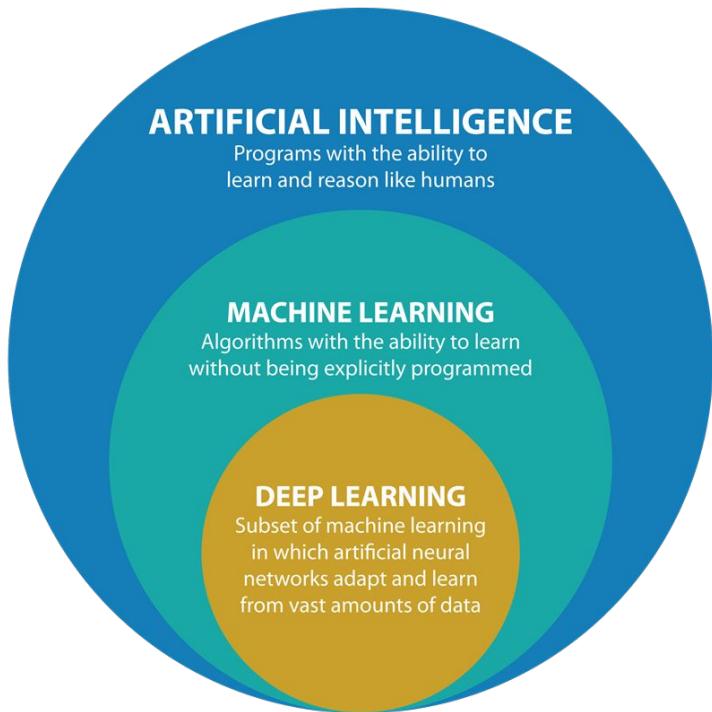
Meet your business challenges head on with
cloud computing services from Google

Agenda

- Machine Learning Overview
- Use-case of Machine Learning
- How to create Machine Learning
- Machine Learning and Data Scientist
- AI Services in Google Cloud Platform
- Use-case of AI Service in Google Cloud Platform
- Demonstration

Machine Learning Overview

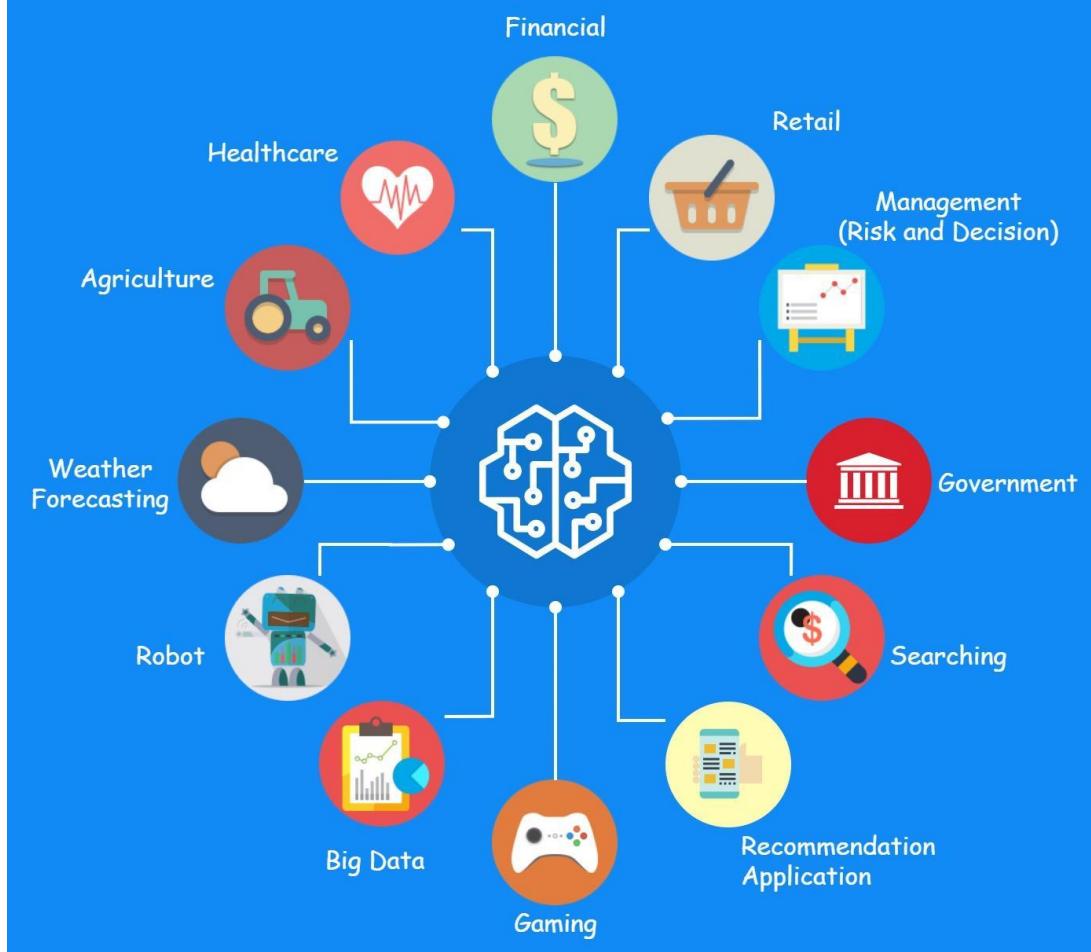
Machine Learning Overview



"Machine learning (ML) is a subfield of artificial intelligence (AI). The goal of ML is to make computers learn from the data that you give them."

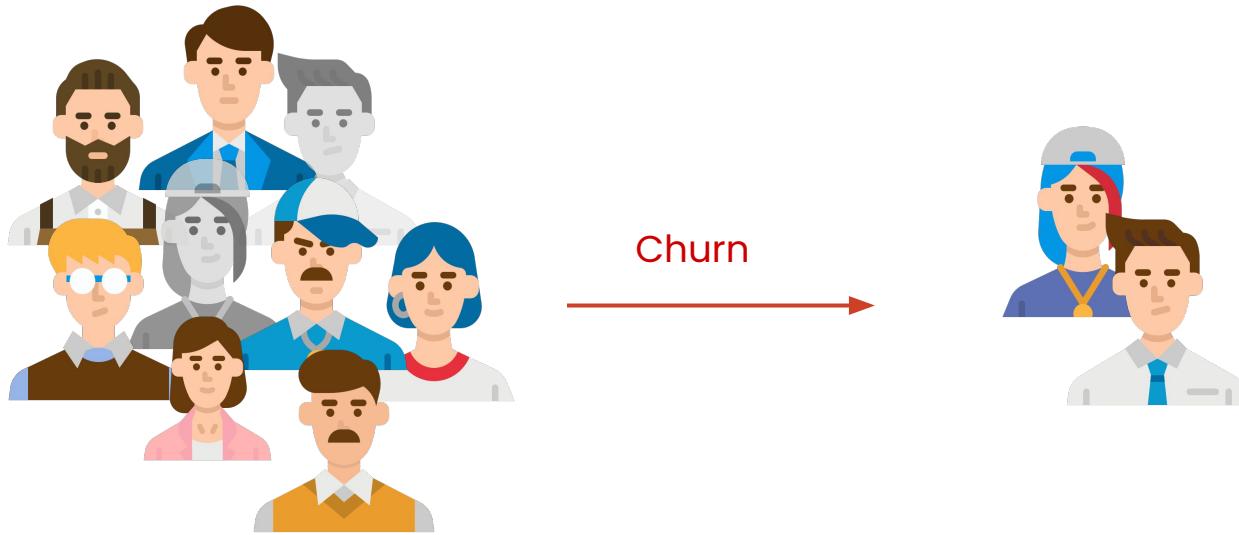
– Google Cloud –
(AI Platform Service)

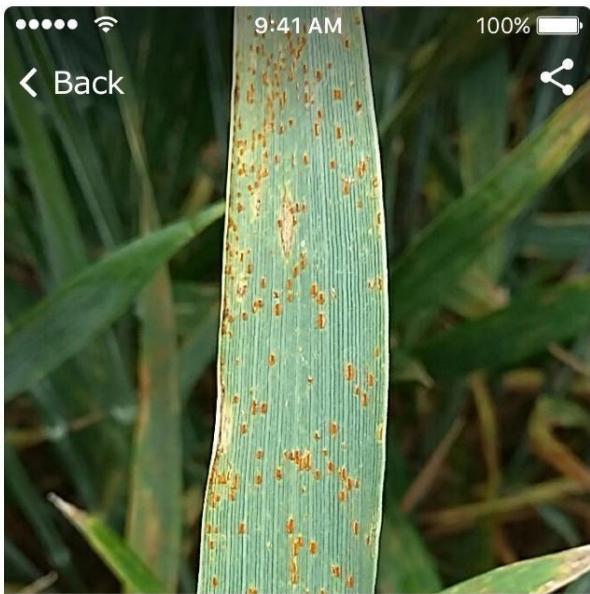
Industries applied Machine Learning



Use case of Machine Learning







Selected disease result



Brown Rust

Puccinia Triticina

91%



Trips



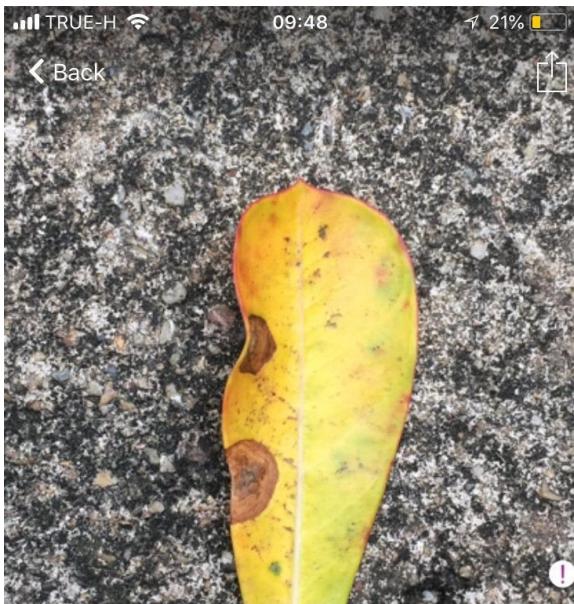
Radar



Notifications



Menu



28/8/2561 BE

Scouting trip #3



Map

Result for leaf damage

Our algorithm is not able to provide reliable result. We apologize for the inconvenience.



Trips



Radar



Notifications



Menu

10^{170}

Possible positions

30M

Trained games

ALPHAGO



Lane Status

Direction: Left curve

Curvature 707.1 m

Off center: Right 0.5m

Detected vehicles



How to create Machine Learning



Machine Learning Approached

The Traditional Programming Paradigm

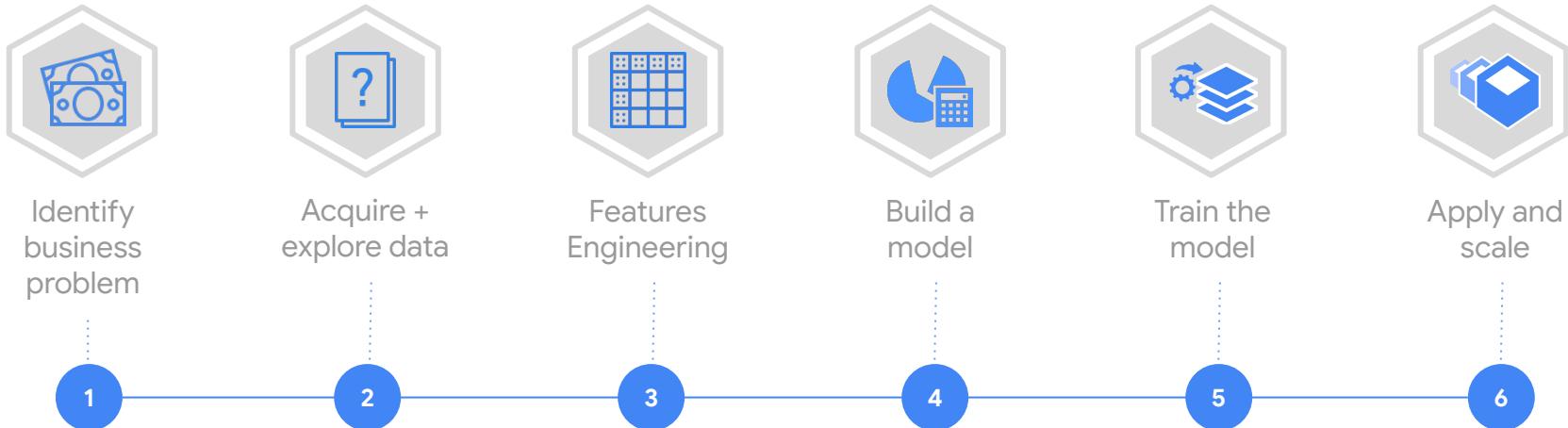


Machine Learning



Sebastian Raschka, 2016

To build a Machine Learning Model

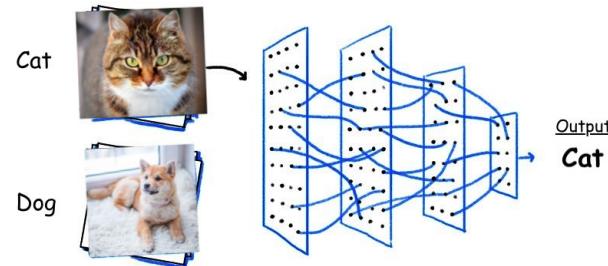


a. Identify business problem

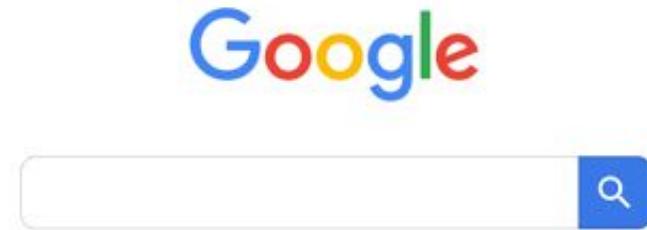
Regression



Classification



b. Data Collection / Data Acquisition



kaggle

IM•GENET

NYC OpenData

c. Feature Engineering

	A	B	C	D	E	F	G	H	I	J
3	Age	Party	Gender	Income		Age	Party 1	Party 2	Gender 1	Income
4	20	Rep	Male	45000		20	1	0	1	45000
5	25	Dem	Male	39000		25	0	1	1	39000
6	45	Ind	Male	56000		45	0	0	1	56000
7	35	Rep	Female	49000		35	1	0	0	49000
8	50	Dem	Female	41000		50	0	1	0	41000
9	55	Ind	Female	42000		55	0	0	0	42000
10	39	Rep	Male	58000		39	1	0	1	58000
11	48	Dem	Male	55000		48	0	1	1	55000
12	30	Ind	Male	46000		30	0	0	1	46000
13	27	Rep	Female	42000		27	1	0	0	42000
14	47	Dem	Female	37000		47	0	1	0	37000
15	21	Ind	Female	25000		21	0	0	0	25000
16	48	Rep	Male	75000		48	1	0	1	75000
17	24	Ind	Male	43000		24	0	0	1	43000
18	28	Ind	Female	40000		28	0	0	0	40000
19	40	Dem	Female	31000		40	0	1	0	31000

c. Feature Engineering (Cont.)

	Country	Age	Salary	Purchased
1	France	44	72000	No
2	Spain	27	48000	Yes
3	Germany	30	54000	No
4	Spain	38	61000	No
5	Germany	40		Yes
6	France	35	58000	Yes
7	Spain		52000	No
8	France	48	79000	Yes
9	Germany	50	83000	No
10	France	37	67000	Yes

Standardisation

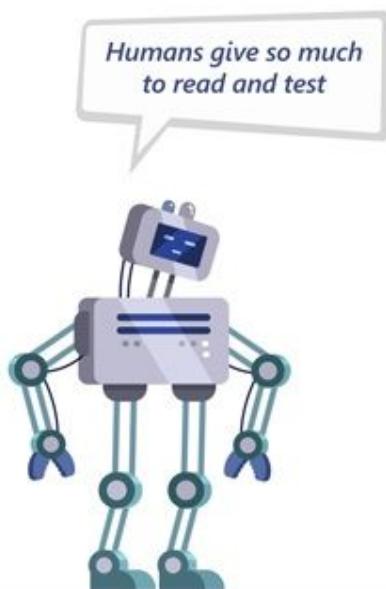
	Age	Salary
0	0.758874	7.494733e-01
1	-1.711504	-1.438178e+00
2	-1.275555	-8.912655e-01
3	-0.113024	-2.532004e-01
4	0.177609	6.632192e-16
5	-0.548973	-5.266569e-01
6	0.000000	-1.073570e+00
7	1.340140	1.387538e+00
8	1.630773	1.752147e+00
9	-0.258340	2.937125e-01

Max-Min Normalization

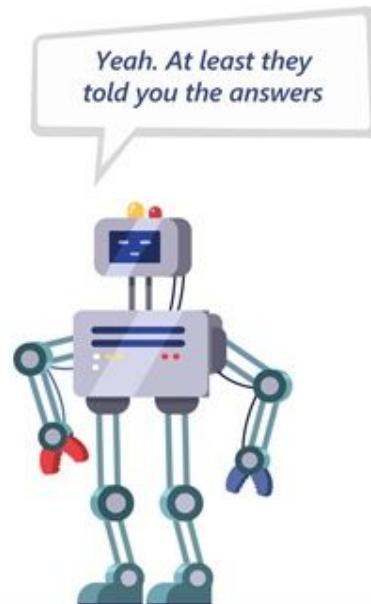
	Age	Salary
0	0.739130	0.685714
1	0.000000	0.000000
2	0.130435	0.171429
3	0.478261	0.371429
4	0.565217	0.450794
5	0.347826	0.285714
6	0.512077	0.114286
7	0.913043	0.885714
8	1.000000	1.000000
9	0.434783	0.542857

d. Build a Model : Machine Learning Type

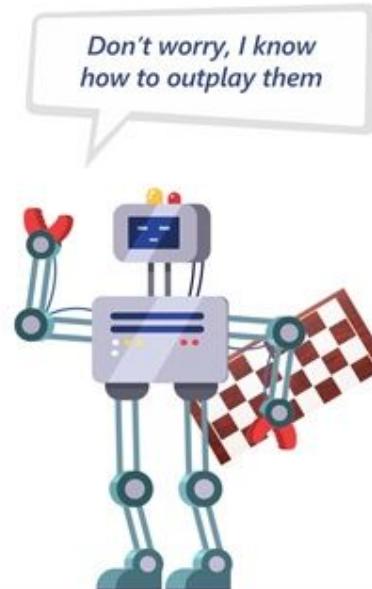
Supervised Learning

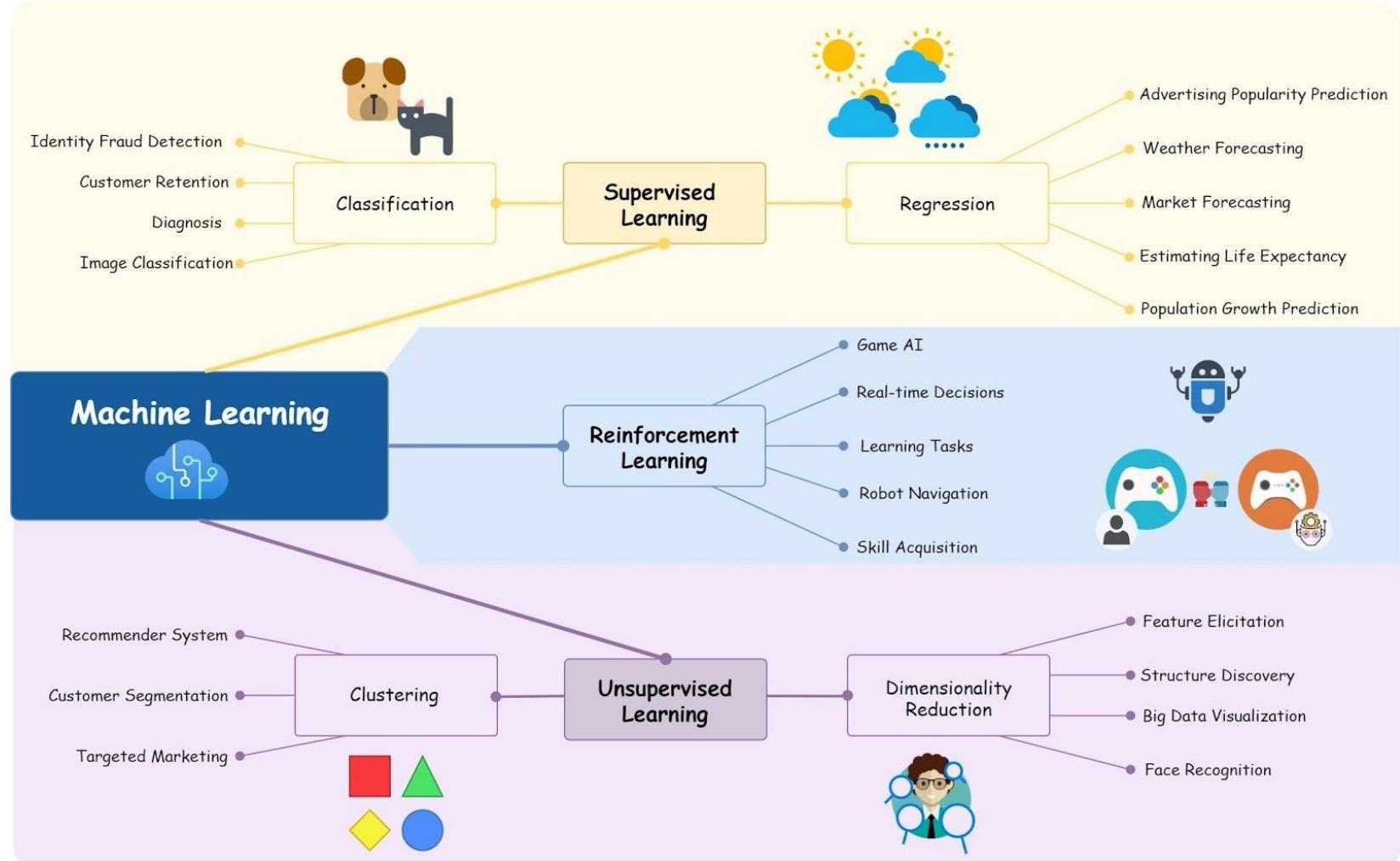


Unsupervised Learning

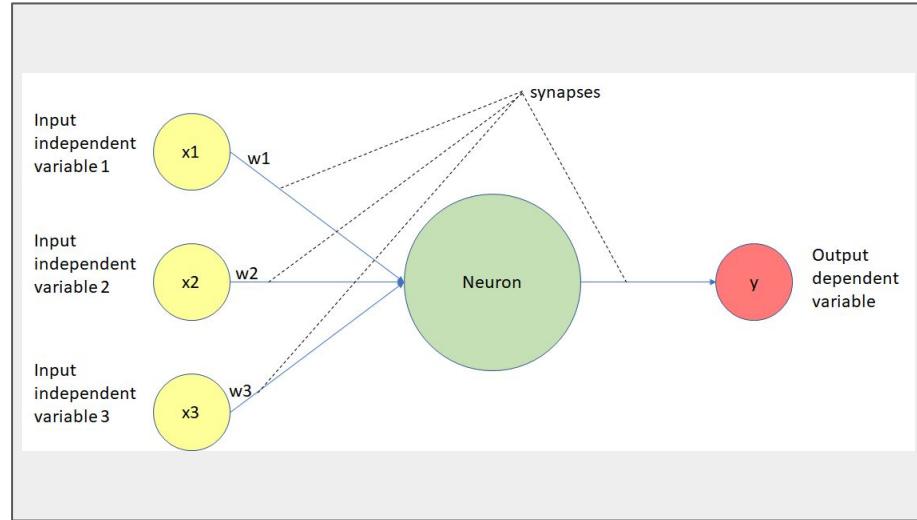
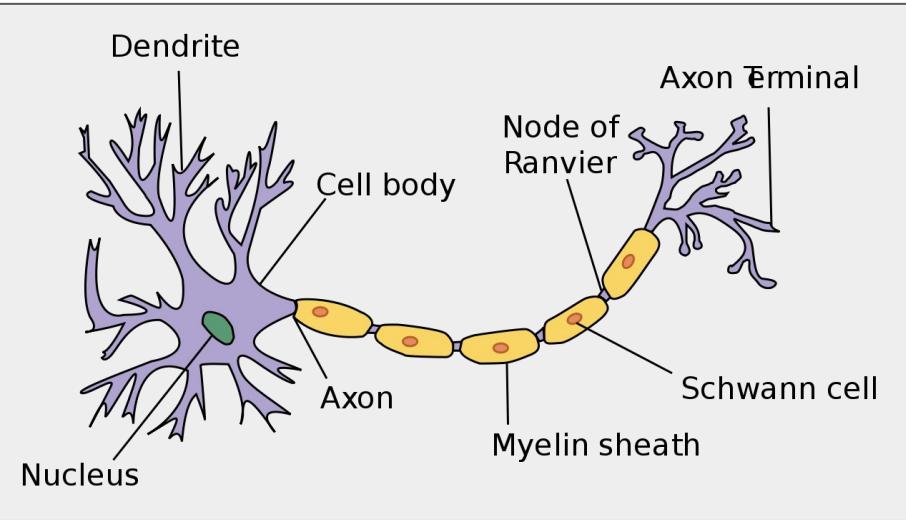


Reinforcement Learning



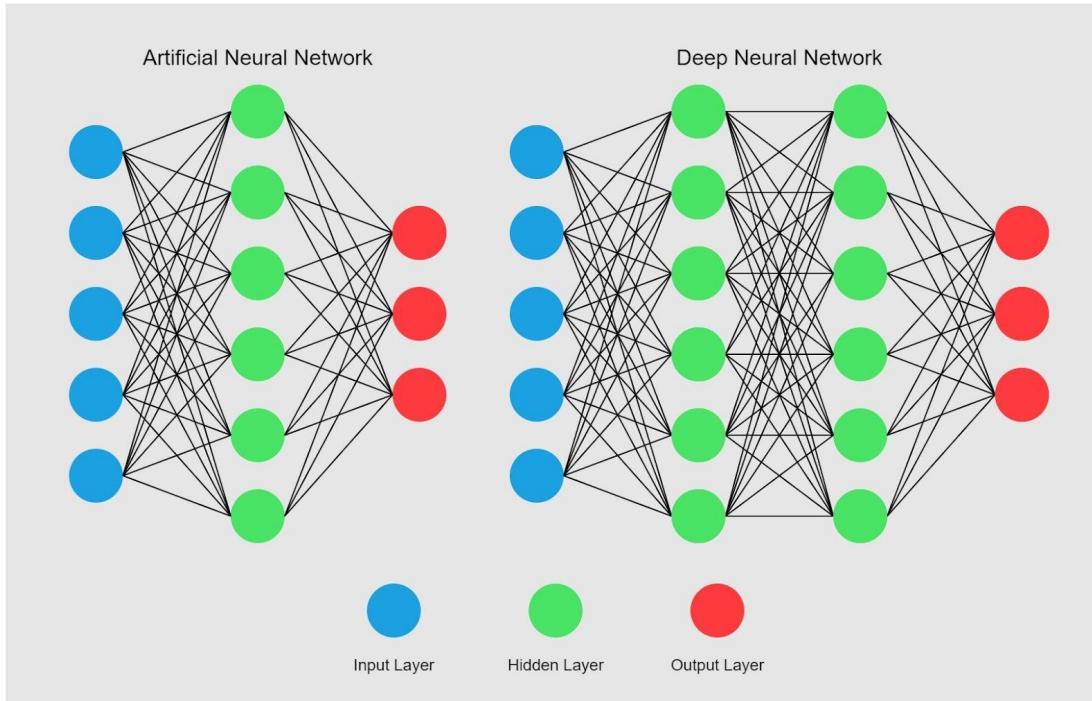


d. Build a Model : Neural Network Concept



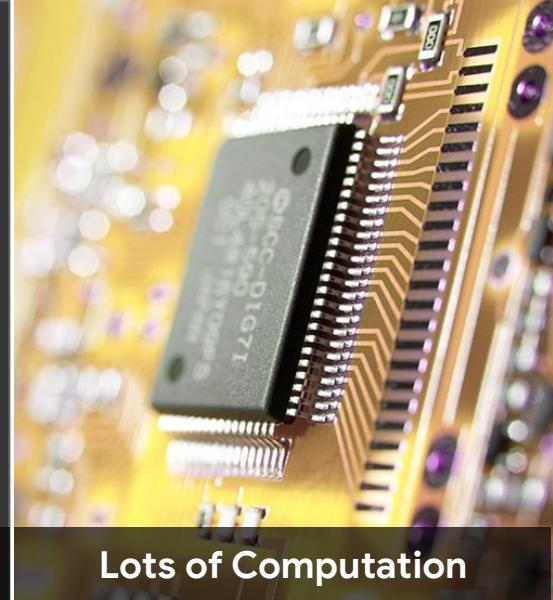
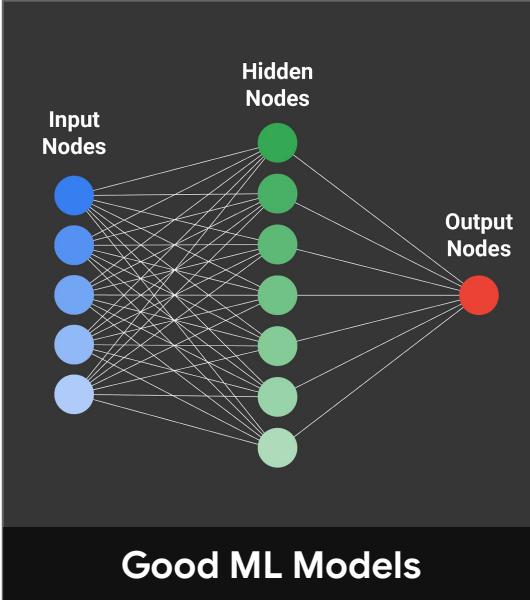
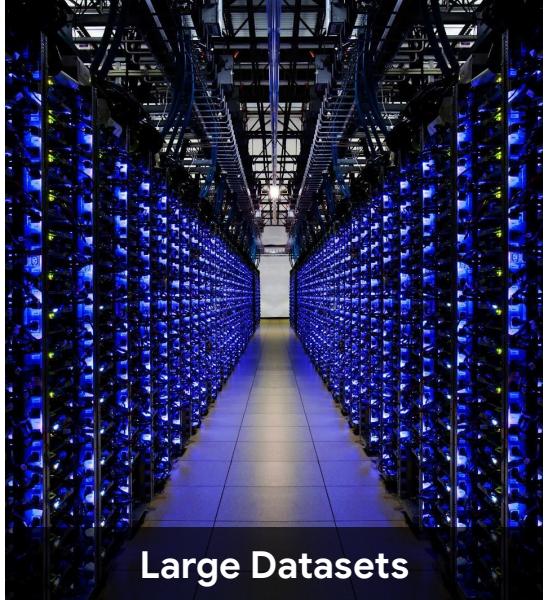
Neuron Network is the network formed by simulating the process of human brain. When human learns something, it will be sent to different parts of the brain to process and generate the result.

d. Build a Model : Neural Network Concept (cont.)

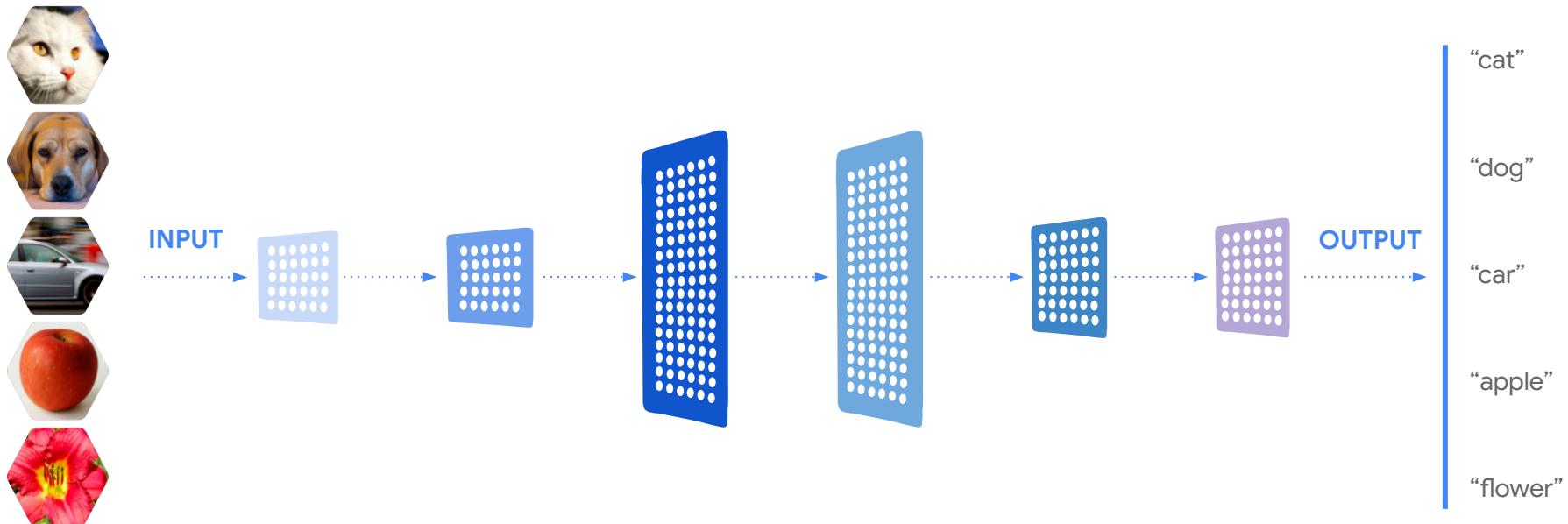


Neural Network is one of Algorithm of Machine Learning which has complex structure

e. Train the Model : Key to Successful ML



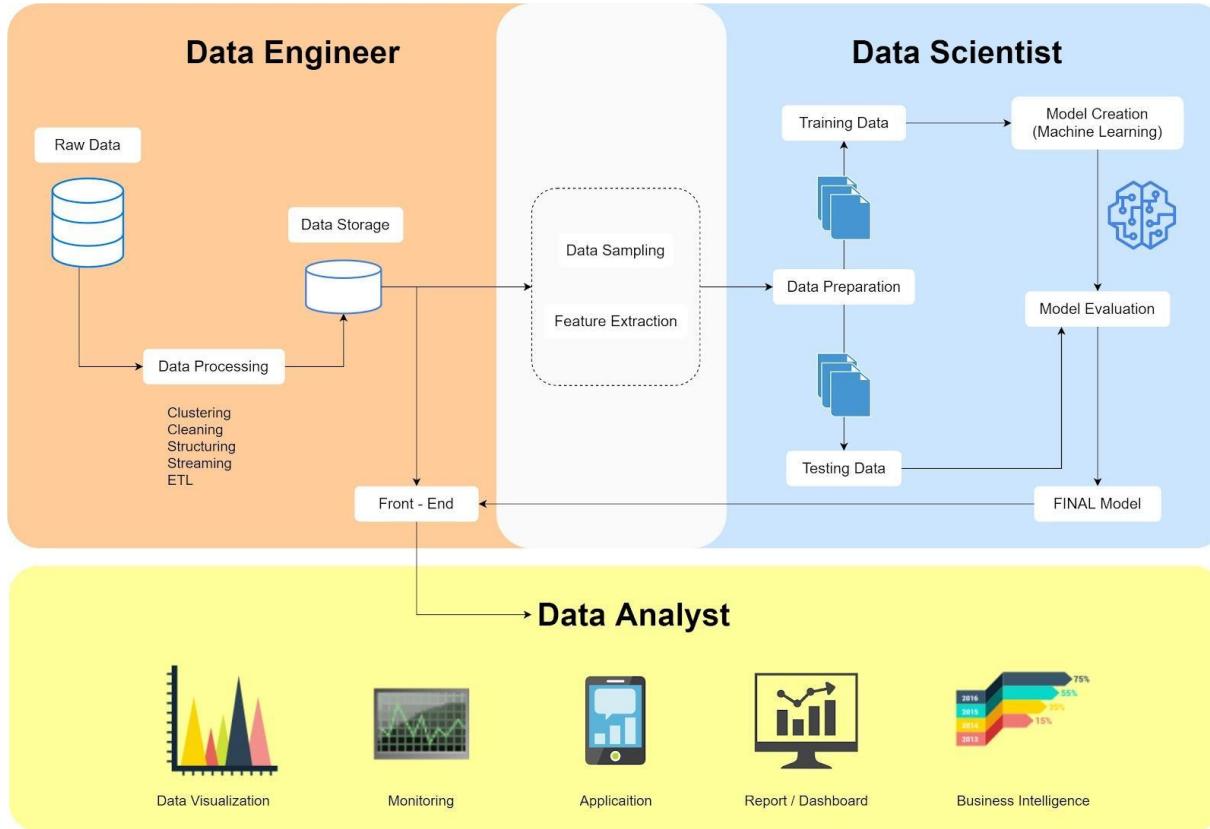
f. Apply and scale



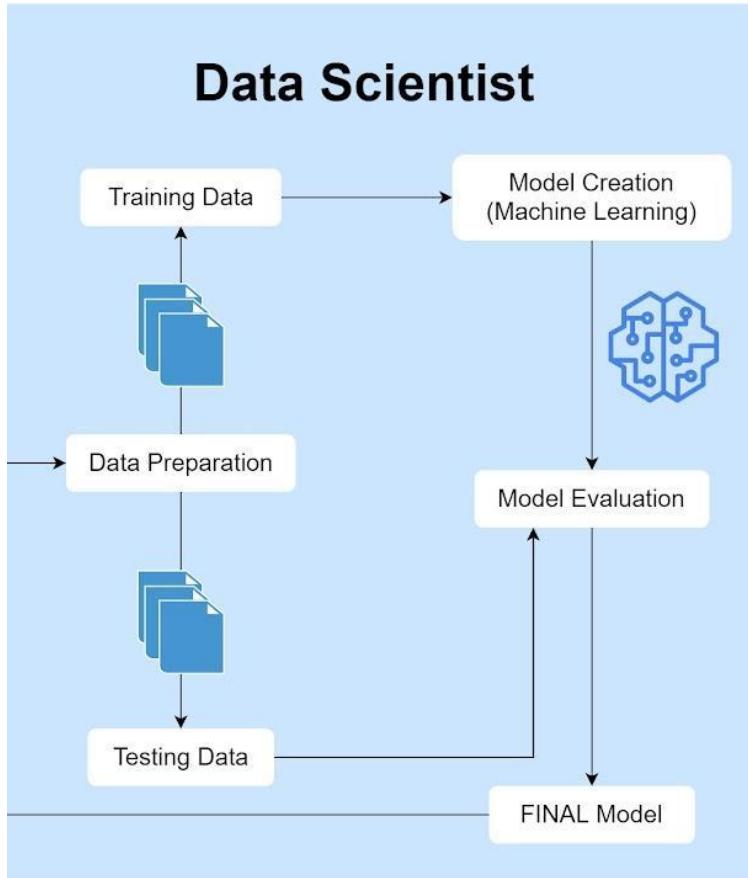
Machine Learning and Data Scientist



Machine Learning and Data Scientist



Machine Learning and Data Scientist



AI Services in Google Cloud Platform



AI Service in Google Cloud

"End-to-end platform for data science and machine learning "

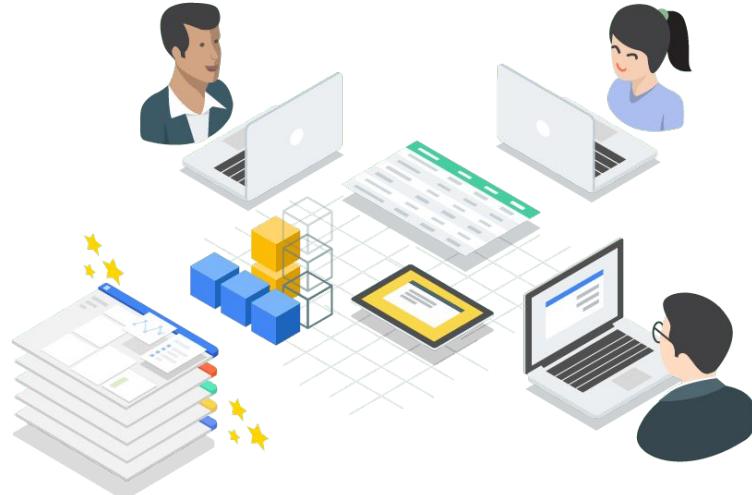
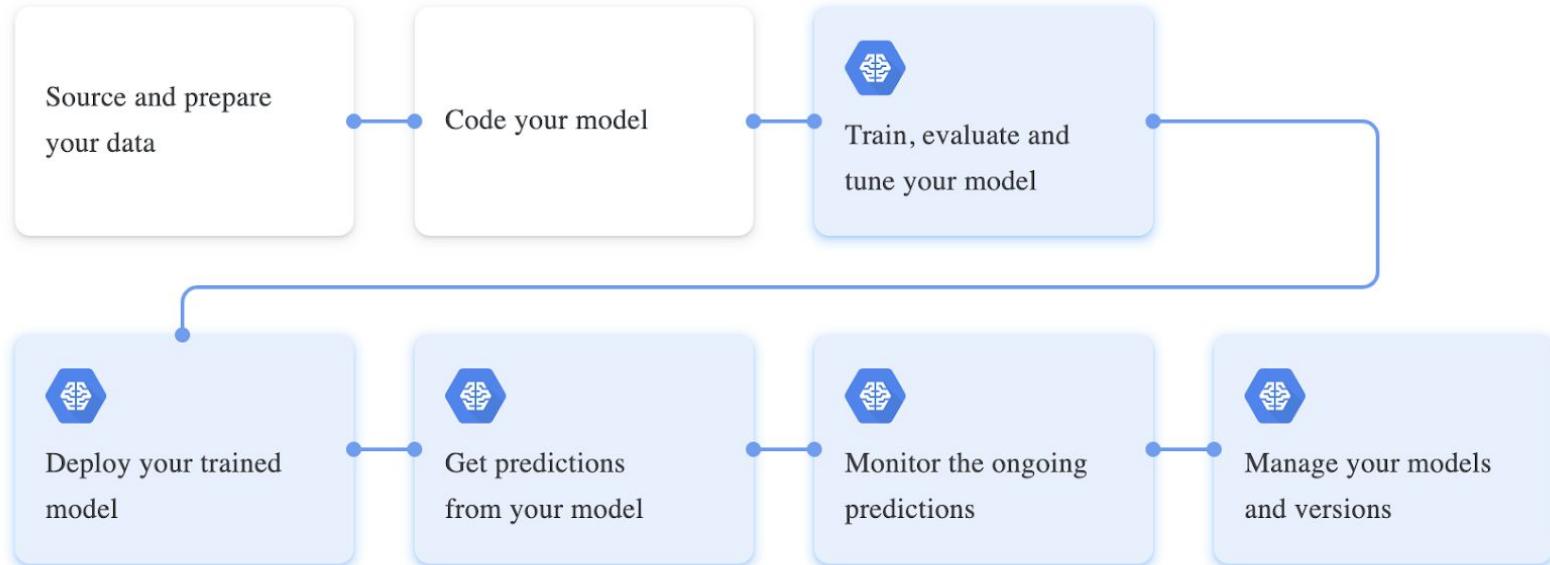
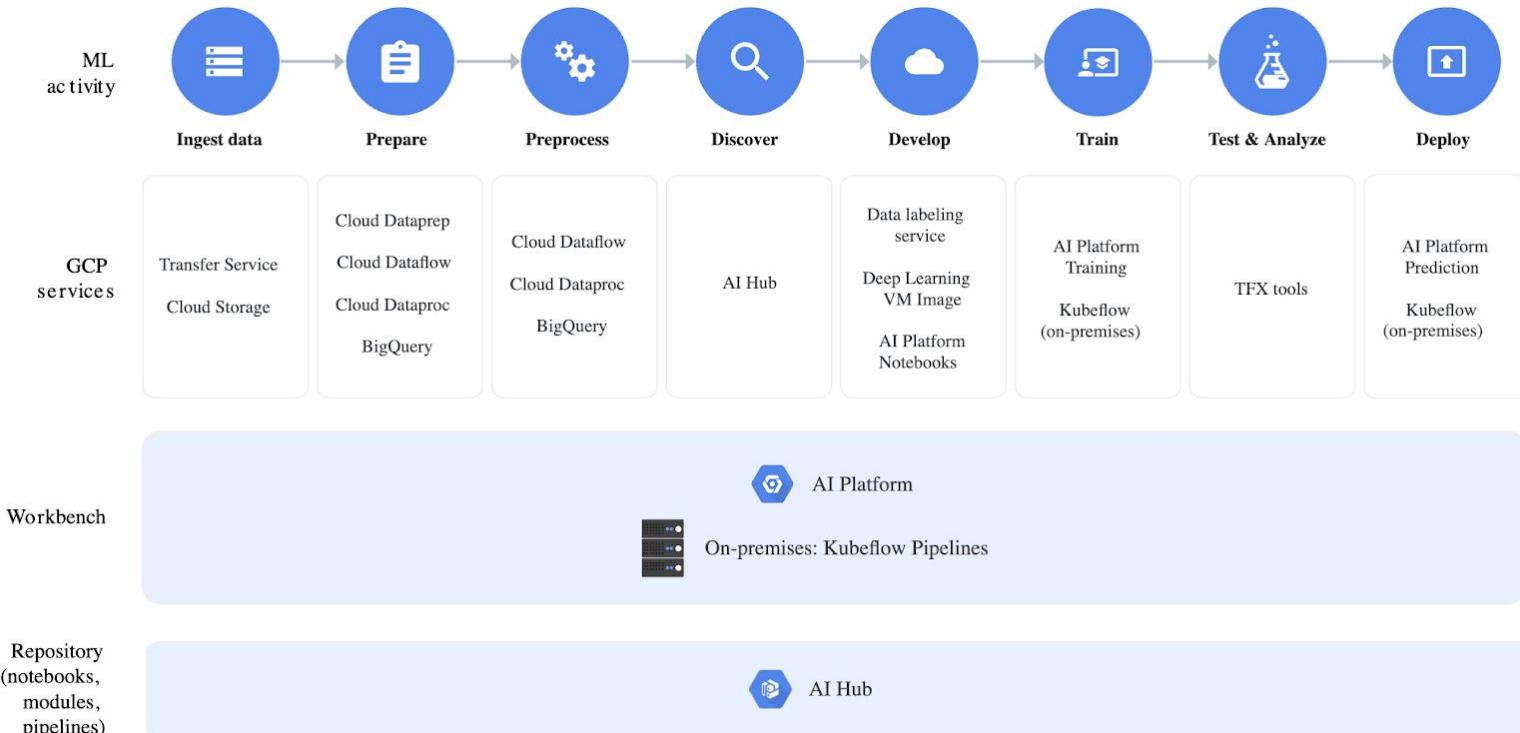


Image from Google

End-to-End in AI Service



Machine Learning Development



Custom ML vs Pre-trained ML

Custom ML models



TensorFlow



Machine Learning
Engine

Pre-trained ML models



Vision API



Speech API



Jobs API



Natural
Language API



Translation
API



Video
Intelligence API

Service for Custom ML



AI Platform



AI Platform
Data Labeling
Service



Cloud
AutoML



AutoML
Translation



AutoML Vision



Cloud TPU



Recommendations
AI



Advanced
Solutions Lab



Cloud
Text-to-Speech



Dialog Flow
Enterprise Edition



AI Hub



AutoML Video
Intelligence



AutoML Natural
Language



AutoML Tables

Google Cloud Platform Icons

AI and Machine Learning



AI Platform



Cloud Vision API



Cloud Speech-to-Text



Cloud Video Intelligence API



Cloud AutoML



Cloud TPU



Cloud Natural Language API



Cloud Translation API



Cloud Jobs API



Advanced Solutions Lab



Cloud Text-to-Speech



Dialog Flow Enterprise Edition



AI Hub



AutoML Video Intelligence



AutoML Natural Language



AutoML Tables



AutoML Translation



AutoML Vision



Recommendations AI



Cloud Inference API



AI Platform Data Labeling Service



AutoML Video
Intelligence



AutoML Natural
Language



AutoML Tables



AutoML
Translation



AutoML Vision

Use case of AI Services in Google Cloud Platform



Example: AutoML Vision

Google Cloud Platform cath-internal-bigdata Search products and resources

Vision Car_Damage LABEL STATS EXPORT DATA

Dashboard Datasets Models

IMPORT IMAGES TRAIN EVALUATE TEST & USE Object detection

	All images	50
<input type="checkbox"/> Select all	Labeled	50
<input type="checkbox"/> Select all	Unlabeled	0
<input type="checkbox"/> Filter labels	damage	50
ADD NEW LABEL		

Filter images

damage(4) damage(1) damage(1)

Images per page: 50 1 – 50 of 50

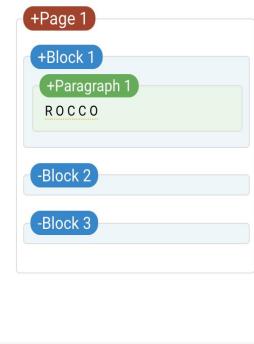
Example: Vision API



Wheel	95%
Wheel	94%
Wheel	94%
Truck	84%

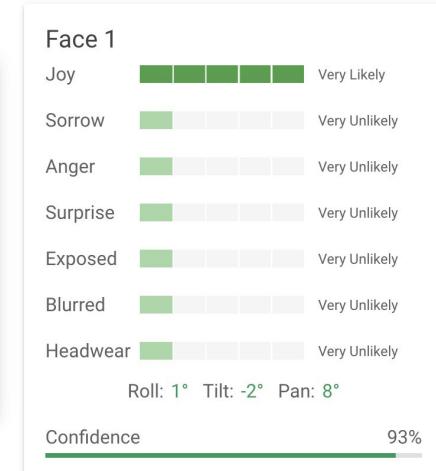
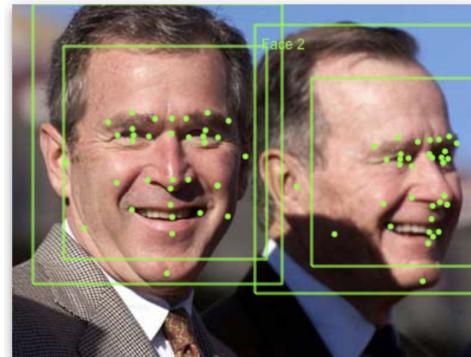
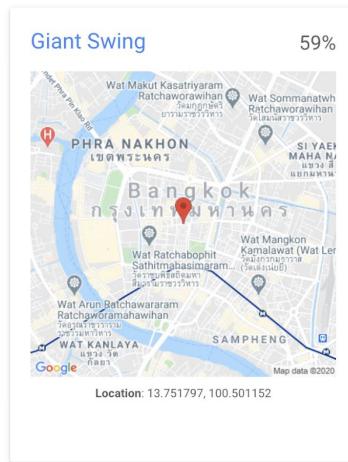


Toyota	98%
--------	-----

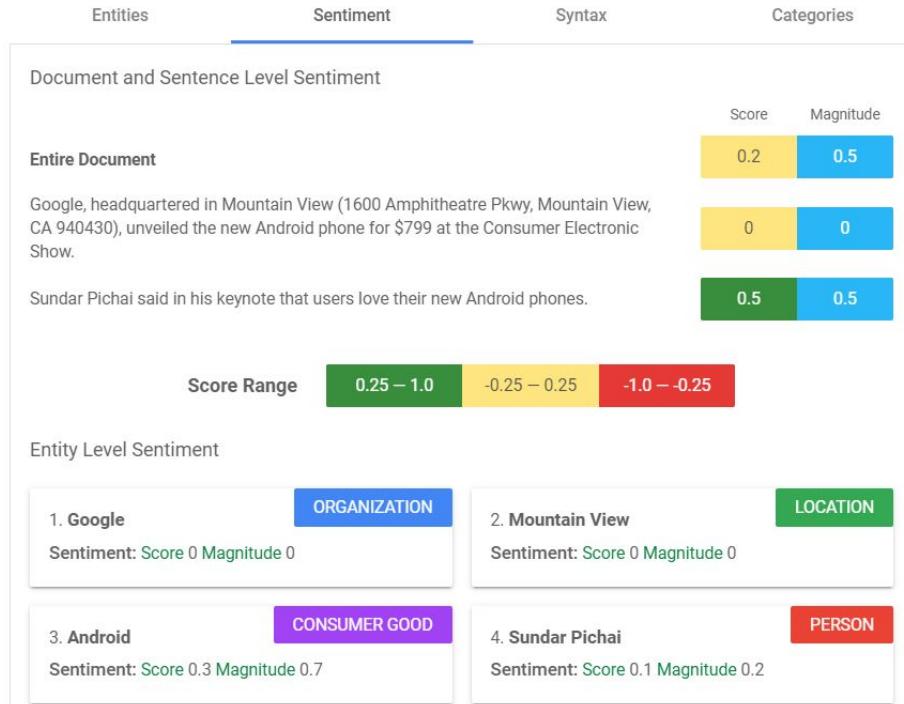


Land Vehicle	100%
Vehicle	99%
Car	99%
Motor Vehicle	97%
Pickup Truck	95%
Automotive Tire	94%
Automotive Design	94%
Toyota	87%

Example: Vision API

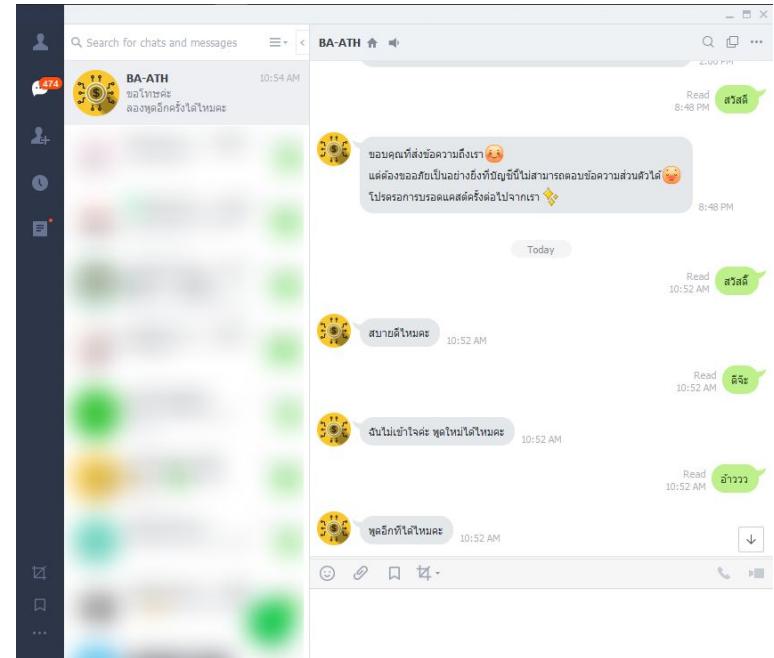


Example: Natural Language



Entities	Sentiment	Syntax	Categories
/Internet & Telecom/Mobile & Wireless Confidence: 0.59			
See a complete list of content categories.			
Entities	Sentiment	Syntax	Categories
(Google) ₁ , headquartered in (Mountain View) ₂ ((1600 Amphitheatre Pkwy, Mountain View, CA) ₁₂ (1600) ₁₅ (Amphitheatre Pkwy) ₇ , (Mountain View) ₂ , (CA 940430) ₈ (940430) ₁₆), unveiled the new (Android) ₃ (phone) ₅ for (\$799) ₁₃ (799) ₁₄ at the (Consumer Electronic Show) ₁₁ . (Sundar Pichai) ₄ said in his (keynote) ₉ that (users) ₆ love their new (Android) ₃ (phones) ₁₀ .			
1. Google	ORGANIZATION		LOCATION
Wikipedia Article			
Salience: 0.19			
2. Mountain View			PERSON
Wikipedia Article			
Salience: 0.18			
3. Android	CONSUMER GOOD		
Wikipedia Article			
Salience: 0.14			
4. Sundar Pichai			PERSON
Wikipedia Article			
Salience: 0.11			
5. phone	CONSUMER GOOD		
6. users			PERSON
Salience: 0.10			

Example: Dialogflow



Break 14:45

Identify Damaged Car Parts with Vertex AutoML Vision

1 hour 30 minutes

5 Credits



GSP972



Google Cloud Self-Paced Labs

BigQuery ML

What is BigQuery ML?



BigQuery

Machine Learning

1

Easy to build and run the model

2

No Python or Java are required

3

High speed of model development

BigQuery ML is a way to build custom models

Build a Custom Model



Cloud TPUs



Compute Engine



Cloud Dataproc



Kubernetes Engine



Cloud AI Platform



BigQuery ML

Build Custom Model (codeless)

AutoML



Call a Pretrained Model



Cloud Translation API



Cloud Vision API



Cloud Speech API



Cloud Video Intelligence API



Data Loss Prevention API



Cloud Speech Synthesis API

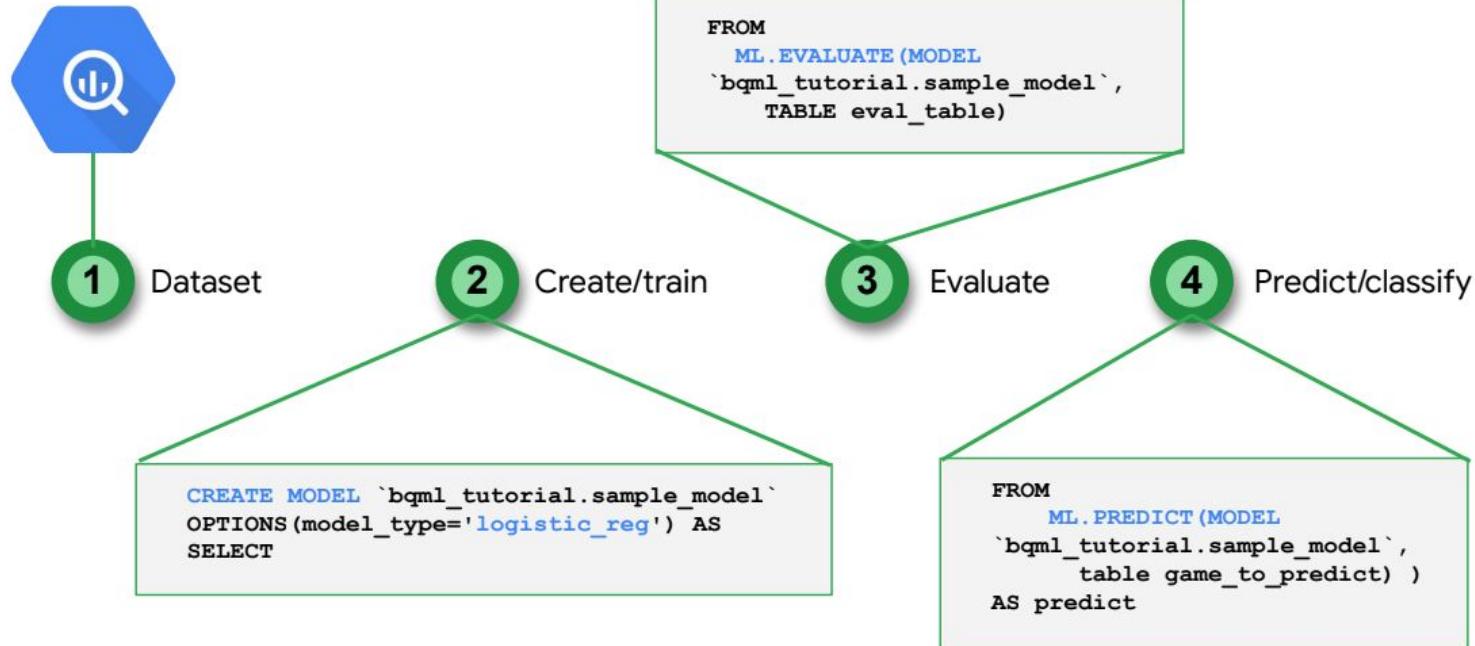


Cloud Natural Language API



Dialogflow

Working with BigQuery ML



Where was this article published?

1

Techcrunch

2

GitHub

3

NY Times

Unlikely Partnership in House Gives Lawmakers Hope for Border Deal

Representatives Nita M. Lowey and Kay Granger are the first women to lead the House Appropriations Committee. Their bond gives lawmakers optimism for the work to come.

By EMILY COCHRANE



Fitbit's newest fitness tracker is just for employees and health insurance members

1 hour ago Jon Russell

Fitbit has a new fitness tracker, but it's one that you can't buy in stores. The company quietly uncorked the Inspire on Friday, releasing its first product that is available only to co...



Downloading the Android Studio Project Folder

FTC Engineering edited this page on Sep 19, 2017 · 1 revision

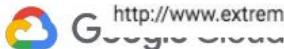
Downloading the Android Studio Project Folder

SQL query to extract data

```
SELECT
    url, title
FROM
    `bigquery-public-data.hacker_news.stories`
WHERE
    LENGTH(title) > 10
    AND LENGTH(url) > 0
LIMIT 10
```

**no clusters, no
indexes, ad hoc query!*

url	title
http://www.bbc.co.uk/news/business-27732743	Vodafone reveals direct government wiretaps
https://www.kickstarter.com/projects/appdocu/a...	Doc – App: The Human Story
http://www.starwebworld.com/android-jelly-bean...	Android Jelly Bean: Streaming Audio Through th...
http://www.myplanetdigital.com/digital_strateg...	Why Canadian Tech Entrepreneurs Need to Man/Wo...
http://startupislandconference.com/index.html	StartupConference June 13. - 16. 2013, HVAR Cr...
http://kopimism.org/	Kopimism Hactivism Meetup Tomorrow (Sunday) in...
http://unearthedgadget.com/xbox-live-gold-2/14...	Xbox Live Gold Membership Is It Really Worth -...
https://evertale.com	Evertale changes the way people remember
http://www.racketboy.com/retro/commodore-amiga...	Commodore Amiga: A Beginner's Guide
http://www.extremetech.com/extreme/156393-cold...	Cold fusion reactor "independently verified"



Use regex to get source + train on words of title

```
## txtclass_words
```

LINK SHARING

```
1 WITH extracted AS (
2   SELECT source, REGEXP_REPLACE(LOWER(REGEXP_REPLACE(title, '([a-zA-Z0-9 $.-]+)', ' ')), " ")
3     FROM
4       (SELECT
5         ARRAY_REVERSE(SPLIT(REGEXP_EXTRACT(url, '.+://(.*/)+/'), '.')) [OFFSET(1)] AS source
6           title
7         FROM
8           `bigquery-public-data.hacker_news.stories`
9         WHERE
10          REGEXP_CONTAINS(REGEXP_EXTRACT(url, '.+://(.*/)+/'), '.com$')
11          AND LENGTH(title) > 10
12        )
13      , ds AS (
14        SELECT ARRAY_CONCAT(SPLIT(title, " "), ['NULL', 'NULL', 'NULL', 'NULL', 'NULL']) AS words
15          extracted
16        WHERE (source = 'github' OR source = 'nytimes' OR source = 'techcrunch')
17      )
18      SELECT
19        source,
20        words[OFFSET(0)] AS word1,
21        words[OFFSET(1)] AS word2,
22        words[OFFSET(2)] AS word3,
23        words[OFFSET(3)] AS word4,
24        words[OFFSET(4)] AS words
25      FROM ds
```

This query will process 204.

 Run  Save query  Save view  More

This query will process 204.

Query results

 SAVE RESULTS

 EXPLORE IN DATA STUDIO

37293	nytimes	the	socratic	shrink	NULL	NULL
37294	nytimes	still	stuck	in	a	climate
37295	nytimes	as	unlimited	data	plans	are
37296	nytimes	disney	s	neuroscience	advertising	lab
37297	nytimes	hold	that	thought	the	google



Create model

Query to extract
training data

```
CREATE OR REPLACE MODEL advdata.txtclass
OPTIONS(model_type='logistic_reg',
        input_label_cols=['source'])
AS

WITH extracted AS (
    ...
)
, ds AS (
    SELECT ARRAY_CONCAT(SPLIT(title, " "), ['NULL', 'NULL',
        'NULL', 'NULL', 'NULL']) AS words, source FROM extracted
    WHERE (source = 'github' OR source = 'nytimes' OR source
        = 'techcrunch')
)
SELECT
    source,
    words[OFFSET(0)] AS word1,
    words[OFFSET(1)] AS word2,
    words[OFFSET(2)] AS word3,
    words[OFFSET(3)] AS word4,
    words[OFFSET(4)] AS word5
    FROM ds
```

Evaluate model

```
SELECT * FROM ML.EVALUATE(MODEL advdata.txtclass)
```

precision	recall	accuracy	f1_score	log_loss	roc_auc
0.783	0.783	0.79	0.783	0.858	0.918

(BQML splits the training data and reports evaluation statistics on the held-out set)

Actual labels	Predicted labels				% samples
	github	nytimes	techcrunch		
github	88.8%	5.29%	5.9%	37.83%	
nytimes	6.34%	70.92%	22.74%	31.26%	
techcrunch	5.54%	19.35%	75.11%	30.9%	

Predict using trained model

```
SELECT * FROM ML.PREDICT(MODEL advdata.txtclass,
    SELECT 'government' AS word1, 'shutdown' AS word2, 'leaves'
    AS word3, 'workers' AS word4, 'reeling' AS word5
    UNION ALL SELECT 'unlikely', 'partnership', 'in', 'house',
    'gives'
    UNION ALL SELECT 'fitbit', 's', 'fitness', 'tracker', 'is'
    UNION ALL SELECT 'downloading', 'the', 'android', 'studio',
    'project'
))
```

Row	predicted_source	word1	word2	word3	word4	word5
1	nytimes	government	shutdown	leaves	workers	reeling
2	nytimes	unlikely	partnership	in	house	gives
3	techcrunch	fitbit	s	fitness	tracker	is
4	techcrunch	downloading	the	android	studio	project

"Batch prediction"

Supported models in BigQuery ML

- ❖ [Linear regression](#)
- ❖ [Binary logistic regression](#)
- ❖ [Multiclass logistic regression](#)
- ❖ [Matrix Factorization](#)
- ❖ [K-means clustering](#)
- ❖ [Time series](#)
- ❖ [Boosted Tree](#)
- ❖ [Deep Neural Network \(DNN\)](#)
- ❖ [AutoML Tables](#)
- ❖ [TensorFlow model importing](#)

1) Classification model

Linear Classifier (Logistic regression)

```
#standardsql
CREATE OR REPLACE MODEL flights.onetime
OPTIONS
  (model_type='logistic_reg', input_label_cols=['on_time']) AS
SELECT
  IF(arr_delay < 15, 1, 0) AS on_time,
  carrier,
  origin,
  dest,
  dep_delay,
  taxi_out,
  distance
FROM
  `cloud-training-demos.flights.tzcorr`
WHERE
  arr_delay IS NOT NULL
```

1) Classification model

DNN Classifier (alpha)

```
#standardsql
CREATE OR REPLACE MODEL flights.onetime
OPTIONS
  (model_type='dnn_classifier', hidden_units = [47,29,18],
   input_label_cols=['on_time']) AS
SELECT
  IF(arr_delay < 15, 1, 0) AS on_time,
  carrier,
  origin,
  dest,
  dep_delay,
  taxi_out,
  distance
FROM
  `cloud-training-demos.flights.tzcorr`
WHERE
  arr_delay IS NOT NULL
```

1) Classification model

xgboost Classifier (alpha)

```
#standardsql
CREATE OR REPLACE MODEL flights.onetime
OPTIONS
  (model_type='boosted_tree_classifier', input_label_cols=['on_time']) AS
SELECT
  IF(arr_delay < 15, 1, 0) AS on_time,
  carrier,
  origin,
  dest,
  dep_delay,
  taxi_out,
  distance
FROM
  `cloud-training-demos.flights.tzcorr`
WHERE
  arr_delay IS NOT NULL
```

2) Regression model

Linear Regression

```
CREATE OR REPLACE MODEL
    taxi.taxifare_dnn OPTIONS (model_type='linear_reg',
        labels=['fare_amount']) AS
SELECT
    fare_amount,
    hourofday, dayofweek,
    pickuplon, pickuplat, dropofflon, dropofflat,
    passenger_count
FROM
    `taxi.taxi3m`
```

2) Regression model

DNN Regression (alpha)

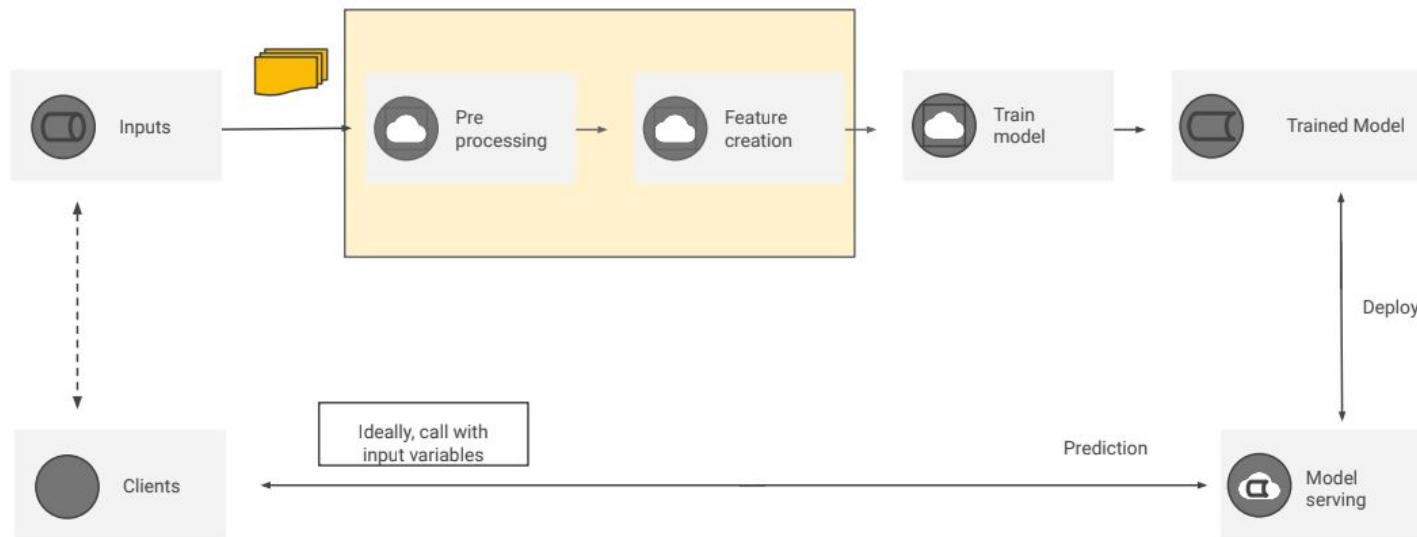
```
CREATE OR REPLACE MODEL
    taxi.taxifare_dnn OPTIONS (model_type='dnn_regressor',
        hidden_units=[144,89,55],
        labels=['fare_amount']) AS
SELECT
    fare_amount,
    hourofday, dayofweek,
    pickuplon, pickuplat, dropofflon, dropofflat,
    passenger_count
FROM
    `taxi.taxi3m`
```

2) Regression model

xgboost Regression (alpha)

```
CREATE OR REPLACE MODEL
    taxi.taxifare_xgboost
    OPTIONS (model_type='boosted_tree_regressor',
        labels=['fare_amount']) AS
SELECT
    fare_amount,
    hourofday, dayofweek,
    pickuplon, pickuplat, dropofflon, dropofflat,
    passenger_count
FROM
    `taxi.taxi3m`
```

Use the transform clause



TRANSFORM ensures transformations are automatically applied during ML.PREDICT

```
CREATE OR REPLACE MODEL ch09edu.bicycle_model  
OPTIONS(input_label_cols=['duration'],  
       model_type='linear_reg')
```

AS

```
SELECT  
    duration  
    , start_station_name  
    , CAST(EXTRACT(dayofweek from start_date) AS STRING)  
        as dayofweek  
    , CAST(EXTRACT(hour from start_date) AS STRING)  
        as hourofday  
FROM  
    `bigquery-public-data.london_bicycles.cycle_hire`
```

```
SELECT * FROM ML.PREDICT(MODEL ch09edu.bicycle_model,(  
    350 AS duration  
    , 'Kings Cross' AS start_station_name  
    , '3' as dayofweek  
    , '18' as hourofday  
))
```



```
CREATE OR REPLACE MODEL ch09edu.bicycle_model  
OPTIONS(input_label_cols=['duration'],  
       model_type='linear_reg')  
TRANSFORM(  
    SELECT * EXCEPT(start_date)  
    , CAST(EXTRACT(dayofweek from start_date) AS STRING)  
        as dayofweek  
    , CAST(EXTRACT(hour from start_date) AS STRING)  
        as hourofday  
)  
AS  
SELECT  
    duration, start_station_name, start_date  
FROM  
    `bigquery-public-data.london_bicycles.cycle_hire`
```

```
SELECT * FROM ML.PREDICT(MODEL ch09edu.bicycle_model,(  
    350 AS duration  
    , 'Kings Cross' AS start_station_name  
    , CURRENT_TIMESTAMP() as start_date  
))
```

BigQuery ML - Free Tier

Resource	Monthly free usage limits	Details
Storage	The first 10 GB per month is free.	BigQuery ML models and training data stored in BigQuery are included in the BigQuery storage free tier.
Queries (analysis)	The first 1 TB of query data processed per month is free.	Queries that use BigQuery ML prediction, inspection, and evaluation functions are included in the BigQuery analysis free tier. BigQuery ML queries that contain CREATE MODEL statements are not. BigQuery flat-rate pricing is also available for high-volume customers that prefer a stable, monthly cost.
BigQuery ML CREATE MODEL queries	The first 10 GB of data processed by queries that contain CREATE MODEL statements per month is free.	BigQuery ML CREATE MODEL queries are independent of the BigQuery analysis free tier, and only apply to BigQuery ML built-in models (models that are trained within BigQuery).



LAB1

Predict Visitor Purchases with a Classification Model in BQML

<https://www.qwiklabs.com/focuses/1794?locale=en&parent=catalog>

