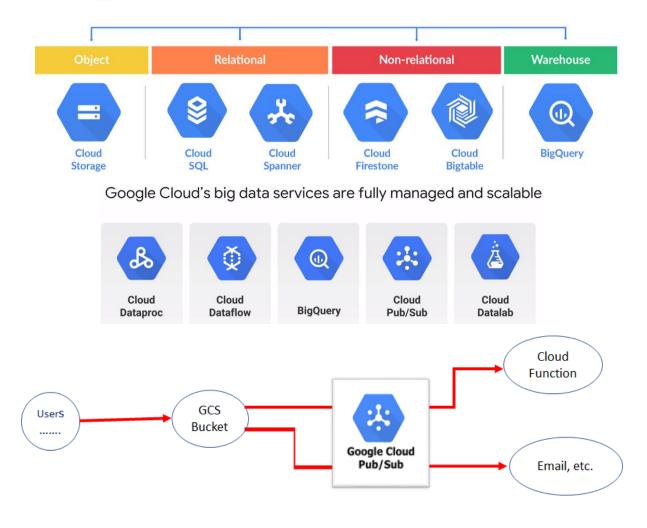


## **Storage & Database Services**



# **Chapter 2: Mastering Python Programming**

Python Statement	Action
x=5	assigns an integer 5 to variable x
y=5.0	assigns a real number 5.0 to variable y
a="hello"	assigns a string "hello" to variable a
b=True	assigns a Boolean value True to variable b

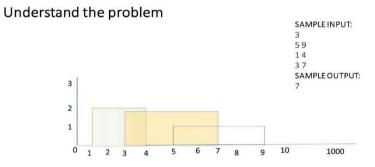
Python Statement	Action
c=x+y	use variable x and y to assign variable c
d=c ** x	use variable x and c to assign variable d

Arithmetic Operation	Syntax	Examples
addition	+	A=x+y
subtraction	-	B=x-y
multiplication	*	C=x*y
division	/	C=x/y
exponentiation	**	E=x**3

Boolean Operation	Syntax	Examples
equal	==	x==y
not equal	! =	x!==y
less than	<	x <y< td=""></y<>
more than	>	x>y
less than or equal	<=	x<=y
more than or equal	>=	x>=y

Logical Operation	Definition	Examples		
and	True if both the operands are true	(x==y) and (a <b)< td=""></b)<>		
or	True if either operand is true	(x==y) or (a <b)< td=""></b)<>		
not	True if the operand is false	not (x==y)		

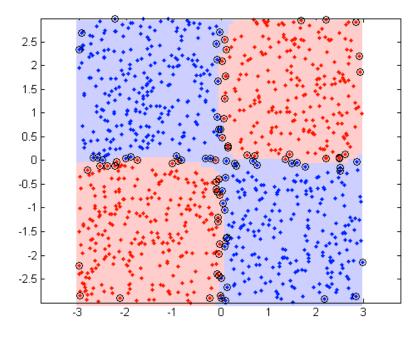
Operation	Defination	Example
len(list)	return the length of the list	len(floats)
list.append(elem)	add an element to the end	floats.append(2.0)
list.pop()	remove the element from the end of list	floats.pop()



# **Chapter 3: Preparing for ML Development**

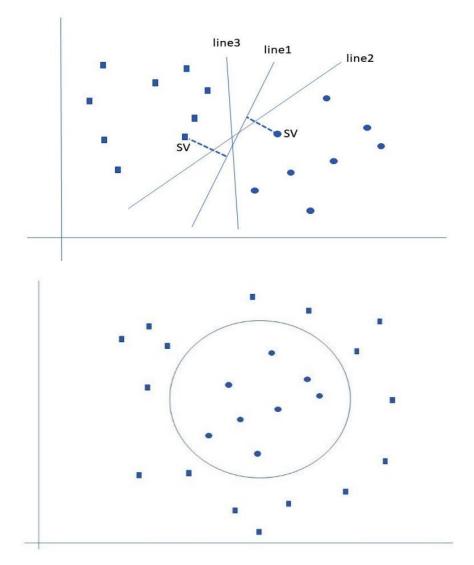
House No	Square Foot	Age	# of Bedrooms	# of Bathrooms	Longitu de	Latitude	Sale Price
1	1500	5	2	1	- 96.698 8856	33.0198 431	250
2	2000	10	3	2	- 96.698 8856	33.0198 431	300
5	3000	40	3	2	- 96.698 8856	33.0198 431	350
10	5500	50	4	3	- 96.698 8856	33.0198 431	450

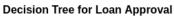
id	color		id	color_red	color_blue	color_green
1	red		1	1	Θ	Θ
2	blue	One Hot Encoding	2	0	1	Θ
3	green		3	Θ	Θ	1
4	blue		4	Θ	1	0

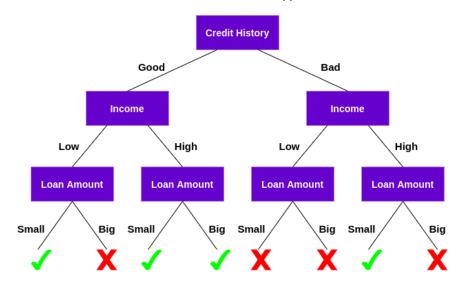


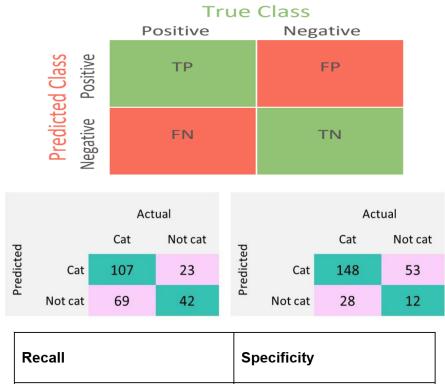
# Chapter 4: Developing and Deploying ML Models

					Bad	kwar	·ds:n	nod	lif	y w a	nd	b	_,		_		
										,							
$ML Model: z^{(i)} = wx^{(i)}$	<sup>(i)</sup> +	<i>b</i> —		<sup>7</sup> ou	vard:	Саси	late	the	m	odel e	erre	or –		the err	or op	timiz	ed?
	Hous	ie No 🗄	Square Foot	(x)	Age B	edRoom	BathRoo	om	Lor	ngitude	La	titude	Sale Price (y, Sk)				
		1	1	1500	5	2		1	-96.	6988856	33.0	)198431	250				
		2	2	2000	10	3		2	-96.	6988856	33.0	)198431	300				
		3	2	2500	20	3		2	-96.	6988856	33.0	)198431	300				
		4	2	2750	10	3		2	-96.	6988856	33.0	198431	400				
		5	3	3000	40	3		2	-96.	6988856	33.0	)198431	350				
		6	3	3500	30	3		2	-96.	6988856	33.0	0198431	375				
		7	4	1000	5	4		3	-96.	6988856	33.0	)198431	450				
		8	4	1500	30	4		3	-96.	6988856	33.0	)198431	400				
		9	5	5000	10	4		3	-96.	6988856	33.0	)198431	450				
		10	5	500	50	4		3	-96.	6988856	33.0	)198431	450				
	No		nt Credit ore		oan unt(\$k)	Annual I (x, \$k)	income	Age		Marriage status	•		al or not (1 , 0 for no)				
-	1	7	30	3	300		150		45		1		1				
-	2	6	70	2	200		100		20		0		1				
-	3	7	00	3	300		50		20		0		0				
-	4	7	80	1	150		80		32		0		1				
-	5	4	00	5	300		20		29		0		0				
-	6	5	00	1	120		70		38		0		1				
-	7	6	90	2	200		140		25		1		1				
-	8	8	23	3	300		150		30		1		1	1			
-	9	4	50	1	100		30		49		1		0	1			
	10	6	50	2	200		120		27		1		1	]			

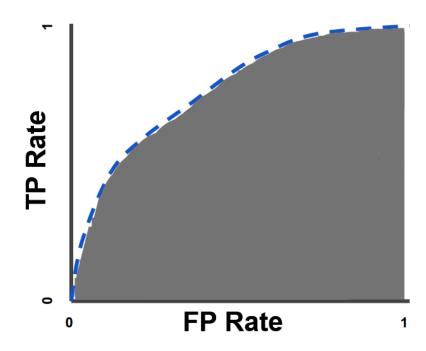


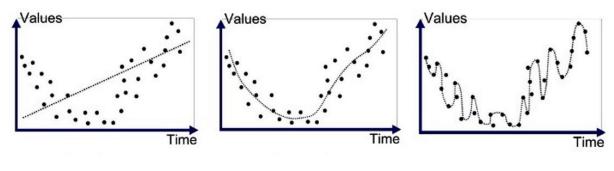






Model 1: 107/ (107+ <u>69)=</u> 60%	Model 1: 42/ (42+ <u>23)=</u> 64%
Model 2: 148/ (148+ <u>28)=</u> 84%	Model 2: 12/ (12+53)=18%



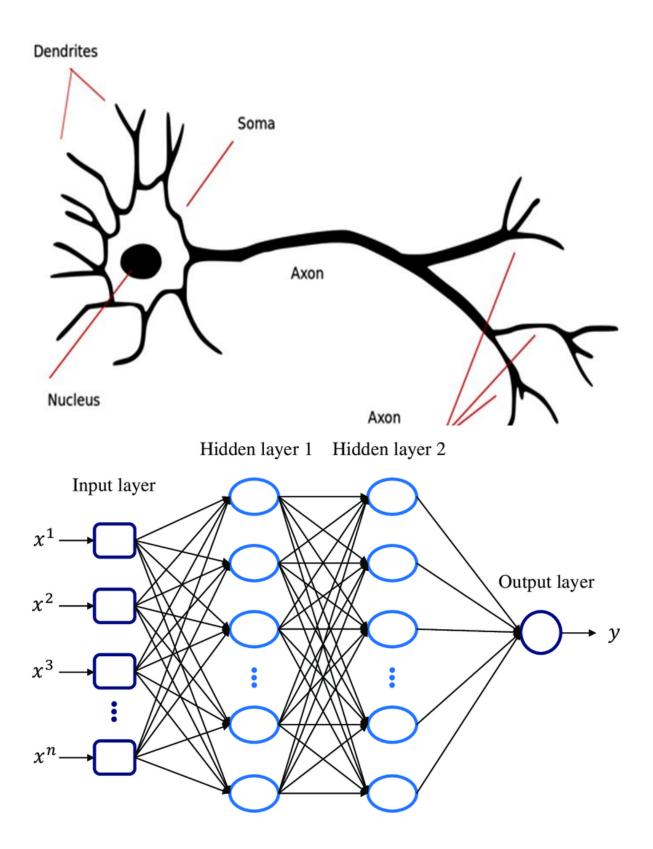


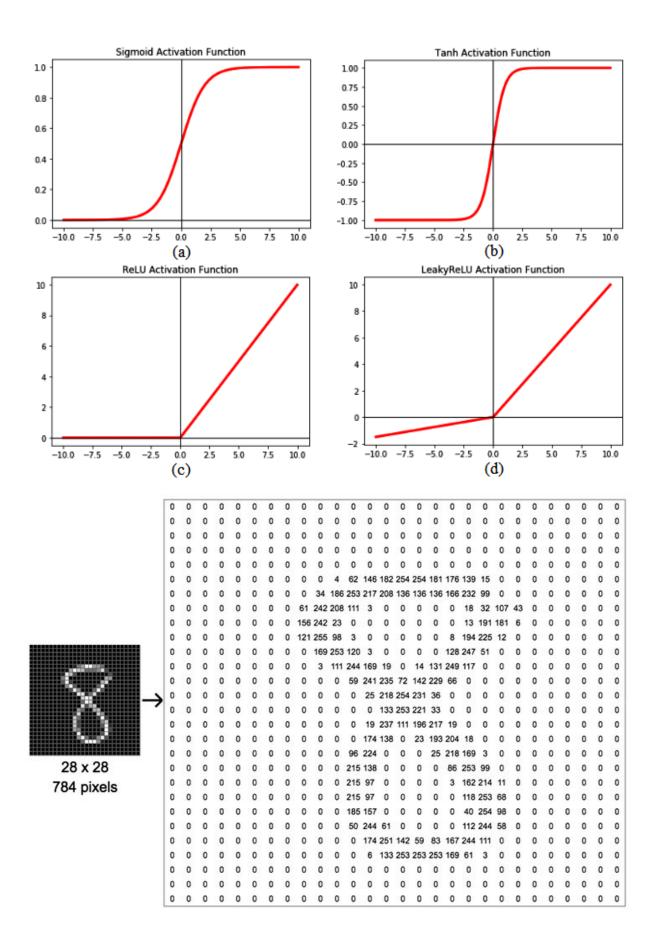
Underfitted

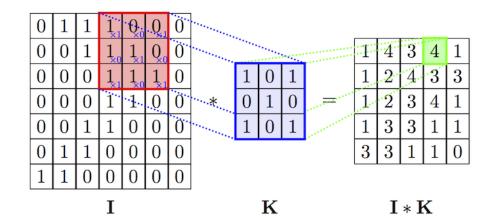
Good Fit/Robust

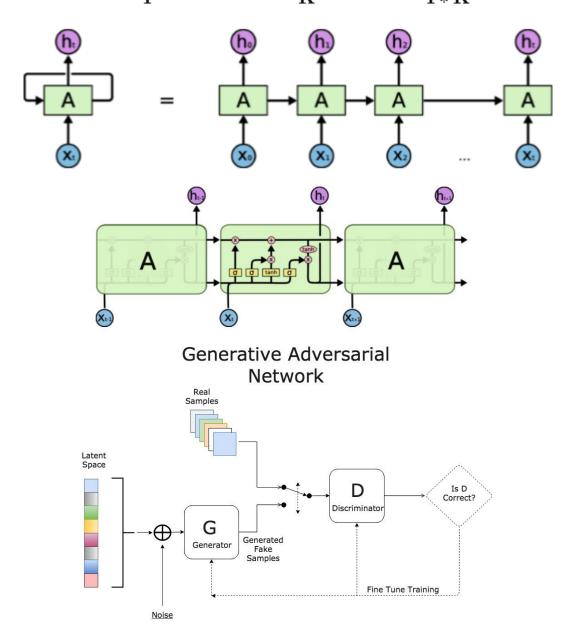
Overfitted

## Chapter 5: Understanding Neural Networks and Deep Learning

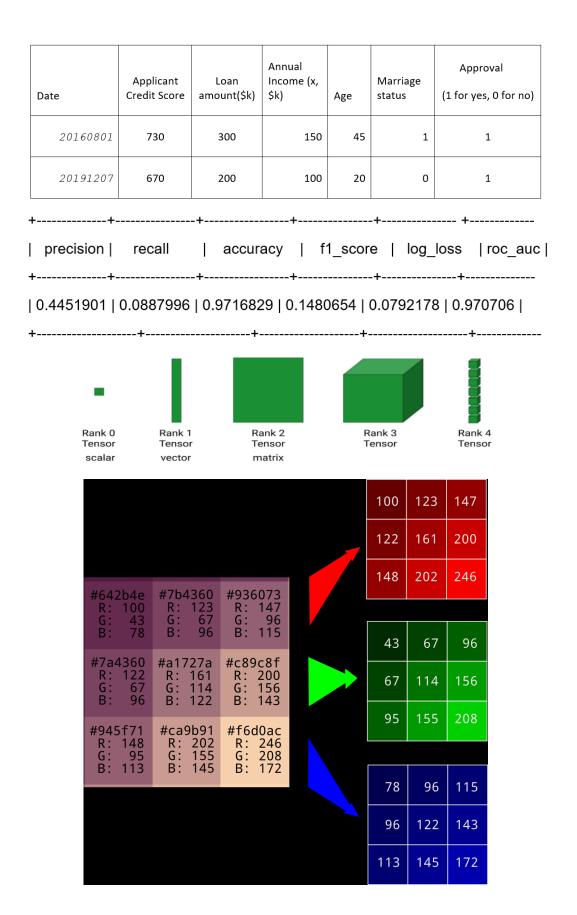








### Chapter 6: Learning BQ/BQML, TensorFlow and Keras

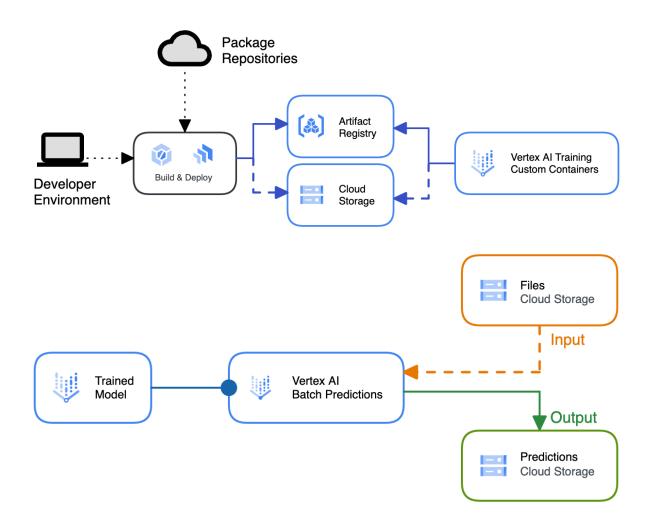


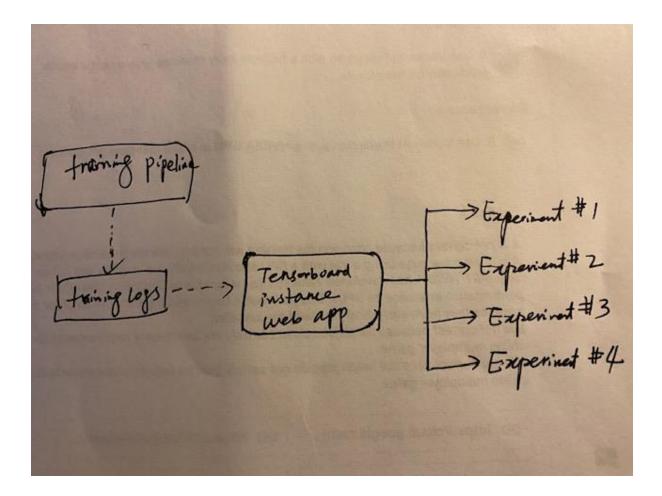
### A tensor is an N-dimensional array of data

Common name	Rank (Dimension)	Example	Shape of example
Scalar	0	<pre>x = tf.constant(3)</pre>	0
Vector	1	x = tf.constant([3, 5, 7])	(3,)
Matrix	2	<pre>x = tf.constant([[3, 5, 7],</pre>	(2, 3)
3D Tensor	3	tf.constant([[[3, 5, 7],[4, 6, 8]], [[1, 2, 3],[4, 5, 6]] ])	(2, 2, 3)
nD Tensor	n	<pre>x1 = tf.constant([2, 3, 4]) x2 = tf.stack([x1, x1]) x3 = tf.stack([x2, x2, x2, x2]) x4 = tf.stack([x3, x3])</pre>	(3, ) (2, 3) (4, 2, 3) (2, 4, 2, 3)

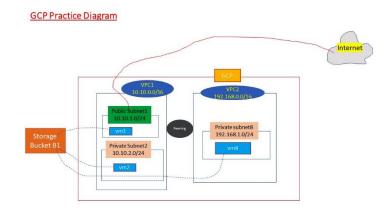
## **Chapter 7: Exploring Google Cloud Vertex AI**

Lucio Custo Conta	ML.	Vertex Al Training Job	Vertex AI Model		
Image data	Tabular data	Text data	Video data		
Classification	Regression	Classification	Action recognition		
Object	Classification	Entity extraction	Video classification		
detection	Forecasting	Sentiment analysis	Video object tracking		





### **Appendix 1 - Practicing with Basic GCP Services**



# Google Cloud

### 🐉 My First Project 👻

▼ vpc1		2	1460	Custom	None			
+ 1001	asia-east1	- subnet2		odotom	10.10.2.0/24	None	None	10.10.2.1
	us-east1	subnet1			10.10.1.0/24	None	None	10.10.1.1
▼ vpc1		2	1460	Custom	None			
	asia-east1	subnet2			10.10.2.0/24	None	None	10.10.2.1
	us-east1	subnet1			10.10.1.0/24	None	None	10.10.1.1
vpc2		1	1460	Custom	None			
	europe- central2	subnet8			192.168.1.0/24	None	None	192.168.1.1

### Create an instance

To create a VM instance, select one of the options:

- New VM instance
   Create a single VM instance from scratch
- H New VM instance from template

Create a single VM instance from an existing template

 New VM instance from machine image Create a single VM instance from an existing machine image

### 2 Marketplace

Deploy a ready-to-go solution onto a VM instance

### Identity and API access @

### Service accounts 💡

Service account Compute Engine default service account

Requires the Service Account User role (roles/iam.serviceAccountUser) to be set for users who want to access VMs with this service account. Learn more

•

#### Access scopes 🔞

- Allow default access
- O Allow full access to all Cloud APIs
- O Set access for each API

#### Firewall @

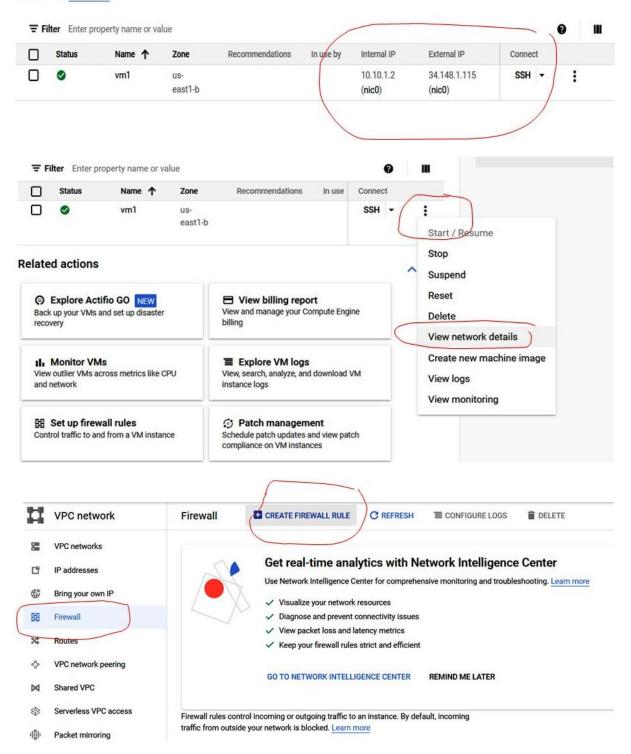
Add tags and firewall rules to allow specific network traffic from the Internet

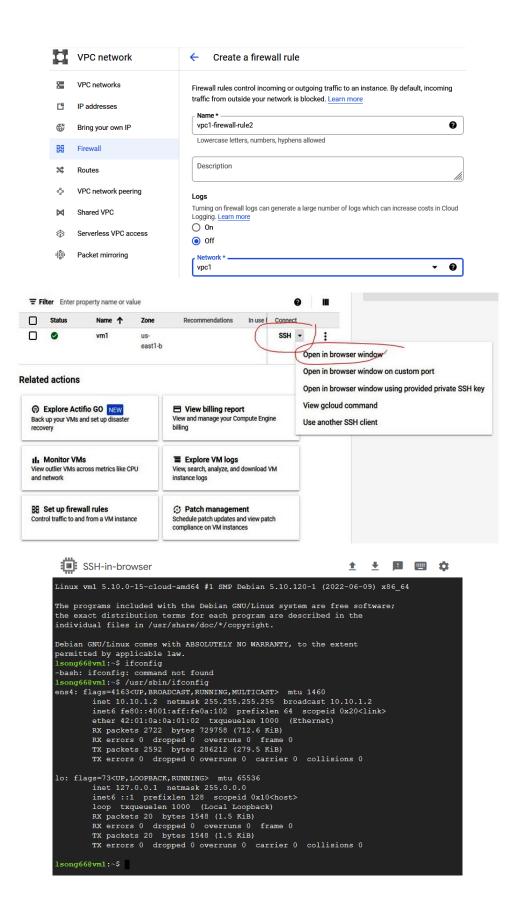
Allow HTTP traffic
 Allow HTTPS traffic

✓ NETWORKING, DISKS, SECURITY, MANAGEMENT, SOLE-TENANCY

	nd network interfaces
Network ta	ags
Hostname	. 0
Set a custo	m hostname for this instance or leave it default. Choice is permanent
P forwardin	ng 🕑
Enable	
letwork	performance configuration
Network int	terface card
-	
letwork bar	ndwidth
and the second se	e total egress bandwidth
faximum ou	tbound network bandwidth: 1Gbps
lotwork	interfaces Ø
Network	Interfaces @
	rface is permanent
default d	efault (10.142.0.0/20)
ADD NET	WORK INTERFACE
Edit net	twork interface
Networ vpc1	к <sup>.,</sup>
	work *
L	
0	To use IPv6, you need an IPv6 subnet range. LEARN MORE
0	To use IPv6, you need an IPv6 subnet range. LEARN MORE
<b>6</b> IP stack	
IP stack	
IP stack	type
IP stack <ul> <li>IP v4</li> <li>IP v4</li> </ul>	type (single-stack)
IP stack IP v4 IP v4 Primary	<b>type</b> I ( <b>single-stack)</b> I and IPv6 (dual-stack)
IP stack IP v4 IP v4 Primary Ephem	type I (single-stack) I and IPv6 (dual-stack) y internal IP neral (Automatic)
IP stack IP v4 IP v4 Primary	type I (single-stack) I and IPv6 (dual-stack) y internal IP neral (Automatic)
IP stack IPv4 IPv4 Primary Epherm	type I (single-stack) I and IPv6 (dual-stack) I internal IP meral (Automatic)
IP stack IP stack IPv4 Primary Epherm Alias IP ( + AD)	type (single-stack) and IPv6 (dual-stack) y internal IP meral (Automatic)
IP stack IP stack IPv4 Primary Epherm Alias IP ( + AD)	type L (single-stack) L and IPv6 (dual-stack) y internal IP eral (Automatic) Tanges D IP RANGE Il IPv4 address
IP stack IP stack IPv4 IPv4 Primary Epherm Alias IP i + ADI Externa Epherm	type (single-stack) I and IPv6 (dual-stack) y internal IP reral (Automatic)
IP stack IP stack IPv4 IPv4 Primary Epherm Alias IP ( + ADI External Epherm Network	type (single-stack) 4 and IPv6 (dual-stack) y internal IP eral (Automatic) Tranges D IP RANGE all IPv4 address eral Service Tier
IP stack IP stack IPv4 Primary Epherm Alias IP ( + ADI Externa Epherm Network IPv4 Primary Primary Epherm Primary	type I (single-stack) I and IPv6 (dual-stack) y internal IP ranges D IP RANGE II IPv4 address reral
IP stack IP stack IPv4 Primary Epherm Alias IP ( + ADI Externa Epherm Network IPv4 Primary Primary Epherm Primary	type (single-stack) 4 and IPv6 (dual-stack) y internal IP eral (Automatic) Tranges D IP RANGE all IPv4 address eral Service Tier
IP stack IP v4 IPv4 Primary Epherm Alias IP 1 + ADI Externa Epherm Network Pren Star	type I (single-stack) I and IPv6 (dual-stack) y internal IP ranges D IP RANGE II IPv4 address reral
IP stack IP stack IPv4 Primary Epherm Alias IP of + ADI Externa Epherm Network Pren Stan Public D	type I (single-stack) I and IPv6 (dual-stack) y internal IP eral (Automatic) Tranges D IP RANGE al IPv4 address teral Service Tier mium ? addrd (us-east1) ?
IP stack IP	type t (single-stack) 4 and IPv6 (dual-stack) y internal IP teral (Automatic) ranges D IP RANGE all IPv4 address teral Service Tier mium @ tdard (us-east1) @ NS PTR Record @
IP stack IP	type 4 (single-stack) 4 and IPv6 (dual-stack) y internal IP meral (Automatic) ranges D IP RANGE al IPv4 address meral * Service Tier mium adard (us-east1) * NS PTR Record * ble for IPv4
IP stack IP stack IP stack IPv4 Primary Ephem Alias IP I Alias IP L Factorial Ephem Network Pren Stan Public D Enat	type 4 (single-stack) 4 and IPv6 (dual-stack) y internal IP meral (Automatic) ranges D IP RANGE al IPv4 address meral * Service Tier mium adard (us-east1) * NS PTR Record * ble for IPv4
IP stack IP v4 IPv4 Primary Ephem Alias IP I + ADI Externa Ephem Network Pren Stan Public D Enat	type 4 (single-stack) 4 and IPv6 (dual-stack) y internal IP meral (Automatic) ranges D IP RANGE al IPv4 address meral * Service Tier mium * startion (us-east1) * NS PTR Record * ble for IPv4

VM instances are highly configurable virtual machines for running workloads on Google infrastructure. Learn more





3	Network interface is permanent					
	Edit network interface		^			
	Network * vpc1	•	0			
	Subnetwork *	•	0			
	To use IPv6, you need an IPv6 subnet range	e. LEARN MORE				
	IP stack type					
	<ul> <li>IPv4 (single-stack)</li> <li>IPv4 and IPv6 (dual-stack)</li> </ul>					
	Primary internal IP Ephemeral (Automatic)	•	0			
	Alias IP ranges + ADD IP RANGE					
5	External IPv4 address None	•	0			
SSH-in-browse	r		1	≛	<u>.</u>	·····
inet 10.10.2 inet6 fe80:: ether 42:01: RX packets 3 RX errors 0 TX packets 3	sbin/ifconfig BROADCAST,RUNNING,MULTICAST> mtu .2 netmask 255.255.255.255 broad 4001:aff:fe0a:202 prefixlen 64 s 0a:0a:02:02 txqueuelen 1000 (Eth 25 bytes 47289 (46.1 KiB) dropped 0 overruns 0 frame 0 38 bytes 42223 (41.2 KiB) dropped 0 overruns 0 carrier 0	dcast 10.10.2 scopeid 0x20< hernet)				
inet 127.0.0 inet6 ::1 p loop txqueu RX packets 2	BACK,RUNNING> mtu 65536 .1 netmask 255.0.0.0 refixlen 128 scopeid 0x10 <host> elen 1000 (Local Loopback) 0 bytes 1548 (1.5 KiB) dropped 0 overruns 0 frame 0</host>					

lsong66@v ens4: fla

lo: flags

TX packets 20 bytes 1548 (1.5 KiB)

\$

```
lsong66@vm2:~$ ping 10.10.1.2
PING 10.10.1.2 (10.10.1.2) 56(84) bytes of data.
64 bytes from 10.10.1.2: icmp_seq=1 ttl=64 time=188 ms
64 bytes from 10.10.1.2: icmp_seq=2 ttl=64 time=184 ms
64 bytes from 10.10.1.2: icmp_seq=3 ttl=64 time=183 ms
64 bytes from 10.10.1.2: icmp seq=4 ttl=64 time=183 ms
^C
--- 10.10.1.2 ping statistics ---
4 packets transmitted, 4 received, 0% packet loss, time 3004ms
rtt min/avg/max/mdev = 183.399/184.599/188.020/1.975 ms
```

TX errors 0 dropped 0 overruns 0 carrier 0 collisions 0

			≡	Google Clo	ud 🐉 i	/ly Fi	rst Project 👻		
			58	Cloud overviev	N	>	PC networks		
				View all produ	cts				
			PINNE Pin yo	ED ur top products he	ere		Ge		
			MORE	PRODUCTS A			~ ~ ~		
			APPLI	CATION INTEGRA	TION		~		
			0	Eventarc			VPC networks	]	
			=)=	API Gateway			IP addresses		
			Ò	Cloud Schedu	ler		Bring your own IP Firewall		
			1111	Cloud Tasks			Routes		
			<u> </u>	Workflows		>	VPC network peering Shared VPC		
			NETW	ORKING			Serverless VPC access		
			н	VPC network		>	Packet mirroring		
	H	VPC network	÷	Create	peering c	oni	nection	•	
	8	VPC networks							
	C <sup>2</sup>	IP addresses		U				the peered VPC network (ful ered VPC network will be	I
	_ ⊕	Bring your own IP		auto	matically crea	ated.			
	₩ EE	Firewall		Name * vpc12-peering					0
				Lowercase lette		yphe	ns allowed		
	*	Routes		Your VPC netwo vpc1	ork *			-	0
	ኇ	VPC network peering							
	X	Shared VPC		eered VPC net In project sr		2514	422		
	$\Leftrightarrow$	Serverless VPC access	C	) In another p	roject				
	ıliği	Packet mirroring		VPC network na vpc2	ame *				-
				Import custo Export custo xchange subne ou can choose t onnection	o import or exp om routes om routes et routes with o import or exp	publ	ic IP 🕑	s over the VPC peering conner : IP over the VPC peering	ction
				Import subr Export subn					
					CANCEL		-		
C networl	k pe	ering	t C	REATE PE		ON	NECTION	C REFRESH	DELET

**Filter** Enter property name or value

Name 🛧	Your VPC network	Peered VPC network	Peered project ID	Status
vpc12-peering	vpc1	vpc2	smiling-cistern-251422	Active
vpc21-peering	vpc2	vpc1	smiling-cistern-251422	Active

lsong66@vml:~\$ ping 192.168.1.2
PING 192.168.1.2 (192.168.1.2) 56(84) bytes of data.
64 bytes from 192.168.1.2: icmp\_seq=1 ttl=64 time=111 ms
64 bytes from 192.168.1.2: icmp\_seq=2 ttl=64 time=110 ms
64 bytes from 192.168.1.2: icmp\_seq=3 ttl=64 time=110 ms

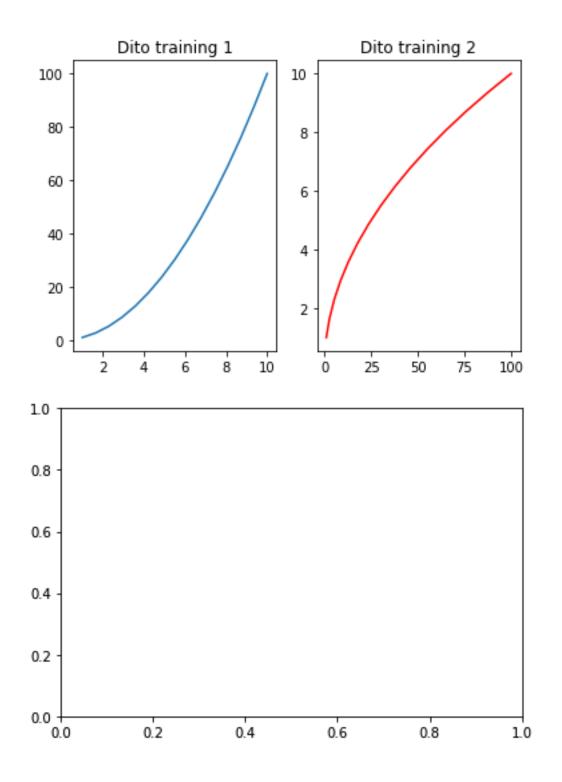
		≡	Goog	l <mark>e</mark> Cloud	ł	🎝 My	Firs	t Project	•	
		51	Cloud	overview		>		rowser		
			View a	II products	S				ilter buck	
		PINN	ED					Name rows to di		
		8	Cloud	Storage		>		Browser	Т	
		MORE	E PRODUC	TS 🔨				Monitorir Settings	ng	
	Cloud	d Storage	Browser	CREATE BUCKET	DELETE	C REFRESH				
۲	Browse	er	<b>∓ Filter</b> Filter bu					•		
ш	Monito	ring	Name ↑ No rows to display	Created Location	on type Loo	ation Default	t storage cla	ass 🤪 Last mo	odified 🕜 Pub	olic access
\$	Setting	S					d by creatin	ore and retrieve y g a bucket – a contain ees to your data and fil	er where you can orgar	nize and

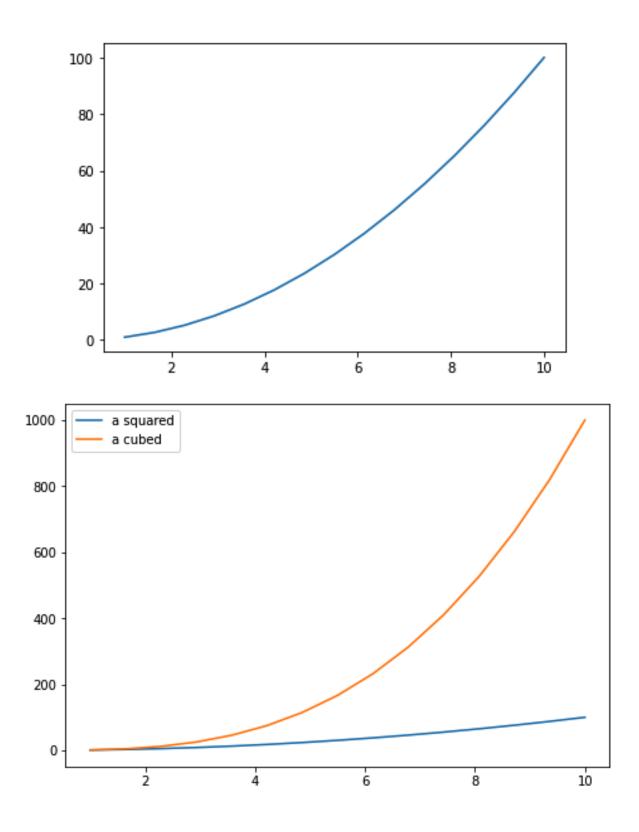
CREATE BUCKET TAKE QUICKSTART

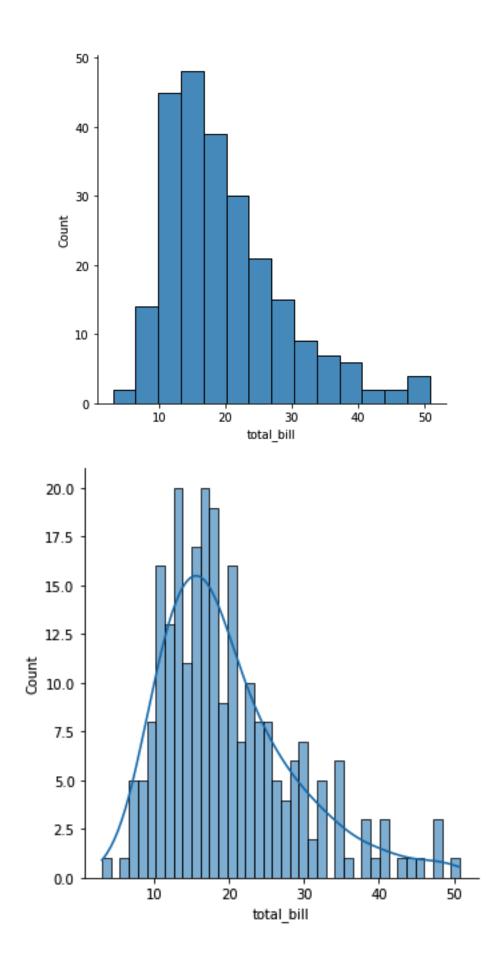
- •	Cloud Storage	<b>←</b> c	Create a bucket	
<b>a</b>	Browser		Name your bucket	
		Pic	Pick a globally unique, permanent name. Naming guidelines	
\$	Settings	Ľ	bucket-08282022	
		T	Tip: Don't include any sensitive information	
		~	LABELS (OPTIONAL)	
			CONTINUE	
		• C	Choose where to store your data	
			This permanent choice defines the geographic placement of your data and affects cost, performance, and availability. Learn more	
			Location type	
		_	Multi-region	
		0	Highest availability across largest area Dual-region	
			High availability and low latency across 2 regions  Region	
			Lowest latency within a single region	
\\$ ;;	Marketplace		us-east1 (South Carolina)	
Cloud Storage	← Bucket details		C REFRESH	ELP ASSISTANT
•				
Browser	bucket-08282022			
Settings	Location Storage cl us-east1 (South Carolina) Standard	Not pul	lic access Protection University None	
octango	OBJECTS CONFIGURATION	PERMISSIO	SIONS PROTECTION LIFECYCLE	
	Buckets > bucket-08282022			
	UPLOAD FILES UPLOAD FOLDER	CREATE F	E FOLDER MANAGE HOLDS DOWNLOAD DELETE	
	_		ojects and folders Show del	
	Name Size Type Cr	eated 🕜	Storage class Last modified Public access 🖗 Version history 🌒 Encryption 🌒 Retention	expiration date 💡

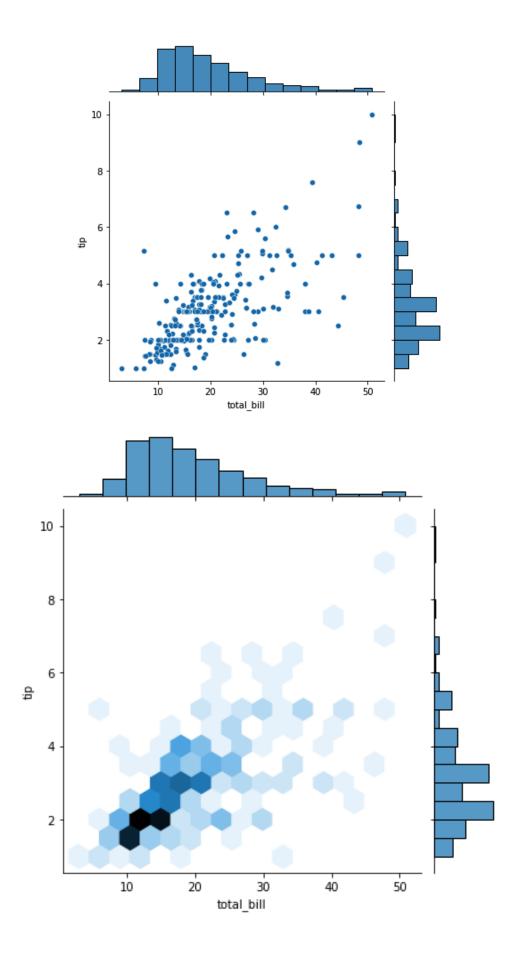
• • • •

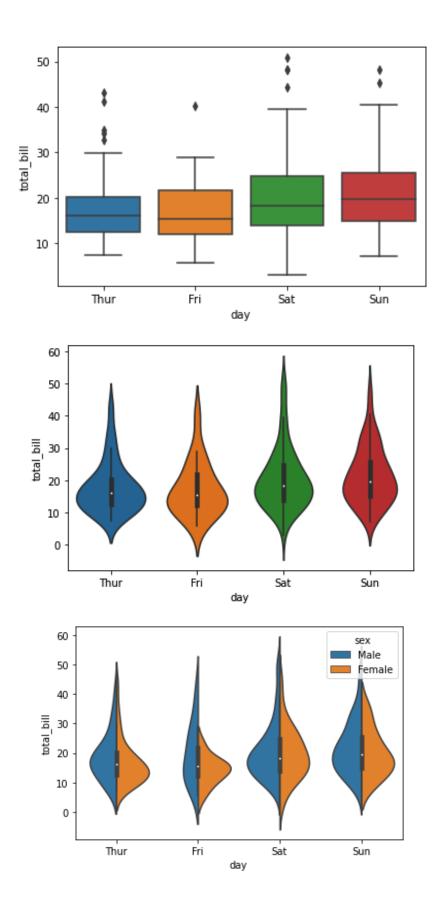
## Appendix 2 - Practicing with Python Data LibraryChapter 13: Getting Started with Power Query







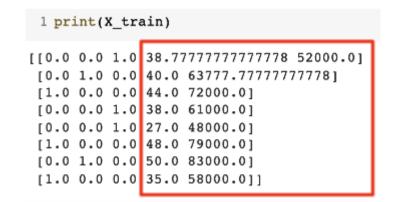


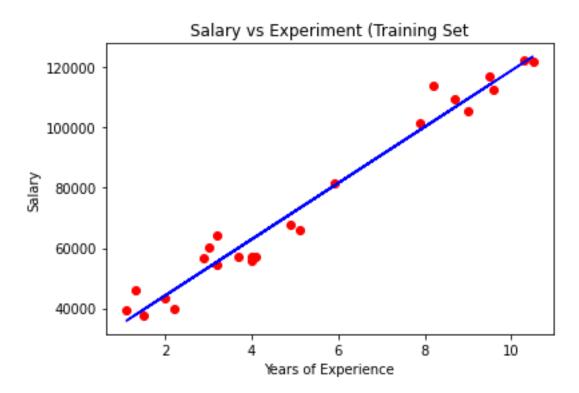


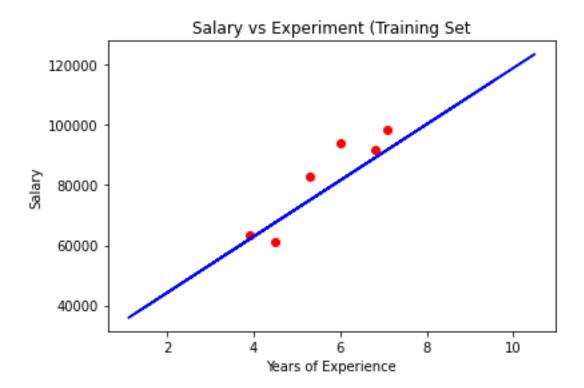
## Appendix 3 - Practicing with ScikitLearnAppendix 2 -Practicing with Python Data LibraryChapter 13: Getting Started with Power Query

Age	Salary	Purchased
44	72000	No
27	48000	Yes
30	54000	No
38	61000	No
40		Yes
35	58000	Yes
	52000	No
48	79000	Yes
50	83000	No
37	67000	Yes
	44 27 30 38 40 35 40 35 48 50	44       72000         27       48000         30       54000         38       61000         40       58000         552000       52000         48       79000         50       83000

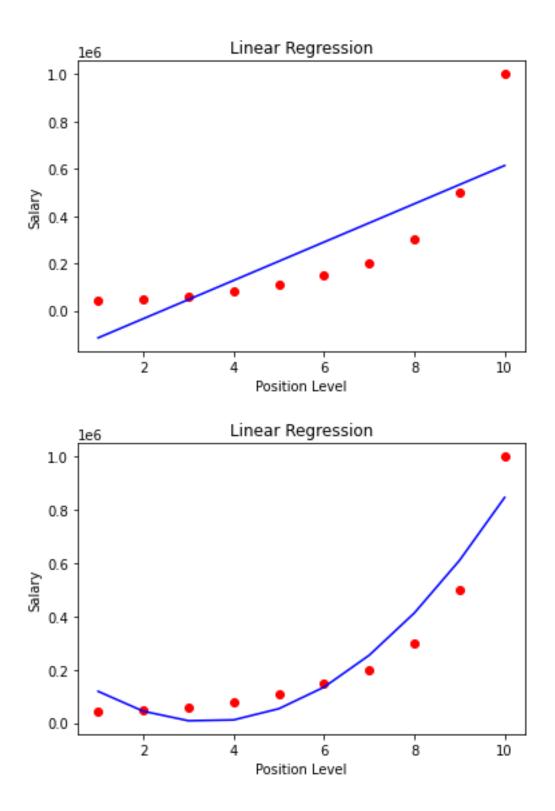
≣	Files			$\square$ ×		+ Cod	le + Text				
Q	A	Ēđ	2	Ø	~ 0	import numpy as np					
{ <i>x</i> }	_	 sample Data.cs			0s		<pre>import numpy as np import pandas as pd import matplotlib.pyplot as plt</pre>				
	-	5				[]					
			$\setminus$								

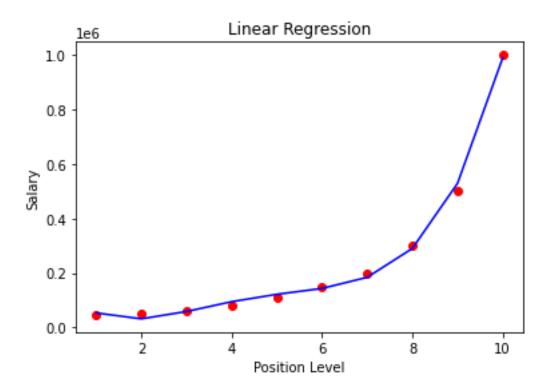






R&D Spend	Administration	Marketing Spend	State	Profit
165349.2	136897.8	471784.1	New York	192261.83
162597.7	151377.59	443898.53	California	191792.06
153441.51	101145.55	407934.54	Florida	191050.39
144372.41	118671.85	383199.62	New York	182901.99
142107.34	91391.77	366168.42	Florida	166187.94
131876.9	99814.71	362861.36	New York	156991.12
134615.46	147198.87	127716.82	California	156122.51
130298.13	145530.06	323876.68	Florida	155752.6
120542.52	148718.95	311613.29	New York	152211.77





Age	EstimatedSalary	Purchased
19	19000	0
35	20000	0
26	43000	0
27	57000	0
19	76000	0
27	58000	0
27	84000	0
32	150000	1
25	33000	0
35	65000	0
26	80000	0
26	52000	0
20	86000	0
32	18000	0
18	82000	0
29	80000	0
47	25000	1
45	26000	1

# Appendix 4 - Practicing with Vertex AI

	Google Cloud Platro	am	Vertex AI - Demo Documer
♠	Home	>	OMMENDATIONS
	View all products		
PINNI Pin yo	ED our top products here		
MORE	PRODUCTS		
	Vertex AI	>	
10	Al Platform	>	Dashboard Datasets
(e=	Data Labeling	>	Features Labeling tasks
R	Document AI	>	Workbench
[≡]	Natural Language		Pipelines
	Recommendations AI	>	Training Experiments
Ë	Retail	>	Models
<b>  </b> •	Speech-to-Text	>	Endpoints
ī	Tables	>	Batch predictions Metadata
2	Talent Solution	>	Matching Engine
Â	Translation	>	
$\diamond$	Vision	>	
152	Video Intelligence	>	

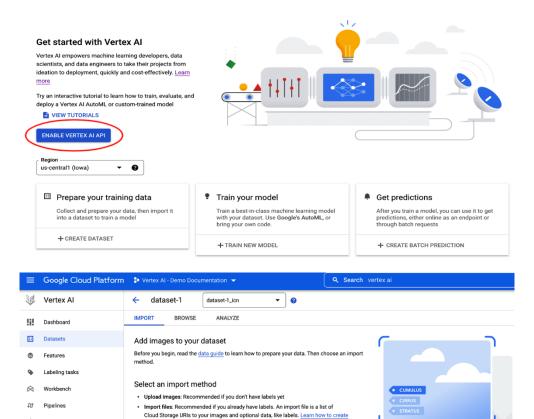


Image classification models predict one (or many) labels for an image. For example, identifying types of clouds from images of the sky.

Instead of creating a custom model, try Google's Vision API to detect generic objects, faces, and text. Learn more 🖄

(¢) Training

x

Models

((e)) Endpoints

ā

Metadata

Experiments

Batch predictions

ုတို့ Matching Engine

an import file

SELECT FILES

Upload images from your computer

O Upload import files from your computer

O Select import files from Cloud Storage

Upload images from your computer

Add up to 500 images per upload. Images will be preprocessed and stored in Cloud Storage.

≡	Google Cloud Platform	🕏 Vertex Al - Demo Documentation 👻 🔍 <b>Q. Search</b> vertex 🛛 🗙 🗴 🖉 🗄 🤗
⇒	Vertex Al	Training CREATE CREATE
51	Dashboard	TRAINING PIPELINES CUSTOM JOBS HYPERPARAMETER TUNING JOBS
	Datasets	Training pipelines are the primary model training workflow in Vertex AI. You can use
۲	Features	training pipelines to create an AutoML-trained model or a custom-trained model. For custom-trained models, training pipelines orchestrate custom training jobs and hyperparameter tuning with additional steps like adding a dataset or uploading the
۹	Labeling tasks	model to Vertex Al for prediction serving. Learn More
$\bigotimes$	Workbench	Region us-central1 (lowa)
£¢	Pipelines	
Ŵ	Training	Filter     Enter a property name     III
x	Experiments	Name ID Status Job type Model type Created Elapsed time Labels
Ŧ	Models	No rows to display
(( <u>@</u> ))	Endpoints	
Ō	Batch predictions	
	Metadata	
ഷ്ട്	Matching Engine	

Tra	in new model	Dataset * dataset-1 (20 images)
0	Training method	ualaset-1 (20 images)
2	Model details	Annotation set * dataset-1_icn
3	Explainability (optional)	Objective
4	Compute and pricing	Image classification (Single-label)
•		Please refer to the pricing guide for more details (and available deployment options) for
STA	ART TRAINING CANCEL	each method.
		Model training method
		AutoML Train high-quality models with minimal effort and machine learning expertise. Just specify how long you want to train. <u>Learn more</u>
		AutoML Edge Train a model that can be exported for on-prem/on-device use. Typically has lower accuracy. Learn more
		Custom training (advanced) Run your TensorFlow, scikit-learn, and XGBoost training applications in the cloud. Train with one of Google Clouds pre-built containers or use your own. Learn more
	(	CONTINUE
	Train new model	Train new model     Creates a new model incurs and assigns the trained model as varion 1
	Training method	Creates a new model group and assigns the trained model as version 1   Train new version Trains model as a version of an existing model
	Model details	Name *
	<ul> <li>Explainability (optional</li> <li>Compute and pricing</li> </ul>	
	START TRAINING CAN	Description
	START IRAINING CAN	Data split
		Randomly assigned Manual (Advanced) Your dataset will be automatically randomized and split into training, validation, and test
		sets using the following ratios. Learn more
		Training         Validation         Constraint         Constrain
		<ul> <li>Training: 80%</li> <li>Validation: 10%</li> <li>Test: 10%</li> </ul>
		Default: 0%
		Encryption Use a customer-managed encryption key (CMEK)
		∧ SHOW LESS
		CONTINUE
ain new r	nodel	Enter the maximum number of node hours you want to spend training your model.
Training n		You can train for as little as 8 node hours. You may also be eligible to train with free nod hours. <u>Pricing guide</u>
Model de	tails	∫ Budget *
Explainab	ility (optional)	10 Maximum node hours
Compute	and pricing	Estimated completion date: Apr 20, 2022 11 AM GMT-4
Compute	priority	Enable early stopping
	G CANCEL	Ends model training when no more improvements can be made and refunds leftover training budget. If early stopping is disabled, training continues until the budget is
		exhausted.

	Google Cloud Platform	🗧 Vertex Al - De	mo Documentation	•			
$\Rightarrow$	Vertex Al	Endpoints	+ CREATE EN				
51	Dashboard	Endpoints are ma	chine learning models	made available f	or online predictio	on requests.	
⊞	Datasets		ful for timely predictio uest). You can also re				
۲	Features	immediate results					
•	Labeling tasks	To create an endp	ooint, you need at least	one machine lea	arning model. <u>Lear</u>	<u>n more</u>	
	Workbench	us-central1 (low	a) 🔻 🕜	J			
Φ	Pipelines	<b>= Filter</b> Enter a	property name				
(¢)	Training	Name		ID	Status	Models	Regio
×	Experiments						
•	Models						
	Endpoints						
ū	Batch predictions						
	Metadata						
ష్టి	Matching Engine						
D D	efine your endpoint	MRI Endpoi	int				e
-	lodel settings	Location					•
2 M	lodel settings	Location		- 0			•
<b>2</b> M	lodel settings	Location Region us-central Access Determines h for prediction the endpoint ( Standard Makes th custom-tr ( Private Create a p	(lowa)	can be acces REST API. Er for prediction e added to sta	serving through ndard endpoints using a VPC ne	a REST API. Aut a.	e availabl ged after toML and

New endpoint	
Ø Define your endpoint	Model settings
2 Model settings	
CREATE CANCEL	Add model Model name* dataset1 • Version Version 1 •
	Traffic split * %
	AutoML image classification and object detection models require a fixed number of compute nodes per model. If you await to change your compute resources for this model in the future, you will have to create a new endpoint. Pricing guide The number of nodes you specify in the input field below will always be ready, and you will be charged continuously for them. Learn more about nodes and prediction cost
	Number of compute nodes *
	Logging Ecology are permanent for this endpoint, and Cloud Logging charges will apply. To change your logging preference in the future, create a new endpoint. Learn more Ecology Ecology and the endpoint Ecology and the en
	It may take several minutes for endpoint settings to take effect.
	ADD AN ITEM

#### Sample Request

	RES	T PYTHON	
Υοι	ıcan	now execute queries using the command line interface (CLI).	
		e sure you have the <u>Google Cloud SDK</u> IZ installed. the following command to authenticate with your Google account.	
	\$	gcloud auth application-default login	6
3.		ate a JSON object to hold your image data. Your image data should be a ba oded string.	se64-
	<b>{</b> }	<pre>"instances": [{     "content": "YOUR_IMAGE_BYTES" }], "parameters": {     "confidenceThreshold": 0.5,     "maxPredictions": 5 }</pre>	6
4.		ate environment variables to hold your endpoint and project IDs, as well as y N object.	our
	\$	ENDPOINT_ID="6619420639025430528" PROJECT_ID="vertex-ai-demo-documentation" INPUT_DATA_FILE="INPUT-JSON"	G
5.	Exe	cute the request.	
	\$	<pre>curl \ -X POST \ -H "Authorization: Bearer \$(gcloud auth print-access- H "Content-Type: application/json" \ https://us-central1-aiplatform.googleapis.com/v1/proj -d "@\${INPUT_DATA_FILE}"</pre>	Б
D	ONE		

### New batch prediction

Batch prediction name \* \_\_\_\_\_\_ batch-prediction-health

Model name \* \_\_\_\_\_ Maternal Health Risk Dataset

Version Version 1

#### Select source

BigQuery table

○ File on Cloud Storage (CSV, JSONL, and TFRecord)

BigQuery path \* \_\_\_\_\_

vertex-ai-demo-documentation.batchprediction.a

Use the following format: projectId.datasetId.tableId. If an optional field is left blank, a new one will be created.

BROWSE

BROWSE

#### Batch prediction output

Select a format and output location for the prediction results

 Output format

 BigQuery table

BigQuery path \* —

vertex-ai-demo-documentation.batchprediction

Use the following format: projectId.datasetId(optional).tableId(optional). If an optional field is left blank, a new one will be created.

#### **Explainability options**

Enable feature attributions for this model

EDIT

➤ ADVANCED OPTIONS

CREATE

CANCEL

#### New notebook

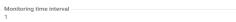
Notebook netobook						
63-char lin with a '-'.	mit with lowerca	se letters, digits, or '-' only. Must start with a letter. Cannot end				
Region *		Zone *				
	(Oregon)	▼ ? Us-west1-b ▼ ?				
Notebool	<pre>c properties</pre>	1				
Environme	nt 🕜	Python 3 (with Intel® MKL)				
Machine ty	/pe	4 vCPUs, 15 GB RAM				
Boot disk		100 GB Standard persistent disk				
Data disk		100 GB Standard persistent disk				
Subnetwor	k	default(10.138.0.0/20)				
External IP	•	Ephemeral(Automatic)				
Permissio	n	Compute Engine default service account				
Estimated	cost 😧	\$102.70 monthly, \$0.141 hourly				
ADVANC	ED OPTIONS	CANCEL				
	Create entit	ty type				
	billing and	1, 2022 at 3:00:00 AM UTC-4, feature value monitoring will begin d remove feature-level monitoring configurations. <u>Learn more about</u> tonitoring changes				

Entity types group and contain related features. For example, a "movies" entity type might contain features like "title" and "genre". Learn more

Region us-central1 (lowa)	
Featurestore *	•
Entity type name *	
Must start with a letter or underscore. Can use letters,	numbers, and underscores.
Description	
Optional text description of the entity type	

Feature monitoring FREVIEW
Provides descriptive statistics and distribution shapes. Enables feature monitoring for all
features in the entity type. You can also edit feature monitoring at the feature level, which
will override this setting.

	Disabled
<u> </u>	



days



#### Overview

This Colab introduces Vertex AI Feature Store, a managed cloud service for machine learning engineers and data scientists to store, serve, manage and share machine learning features at a large scale.

This Colab assumes that you understand basic Google Cloud concepts such as Project, Storage and Vertex AI. Some machine learning knowledge is also helpful but not required.

#### Dataset

This Colab uses a movie recommendation dataset as an example throughout all the sessions. The task is to train a model to predict if a user is going to watch a movie and serve this model online.

#### Objective

In this notebook, you will learn how to:

- \* How to import your features into Vertex AI Feature Store.
- $\ast$  How to serve online prediction requests using the imported features.
- $\ast$  How to access imported features in offline jobs, such as training jobs.

#### Costs

This tutorial uses billable components of Google Cloud:

- Vertex Al
- Cloud Storage
- Cloud Bigtable

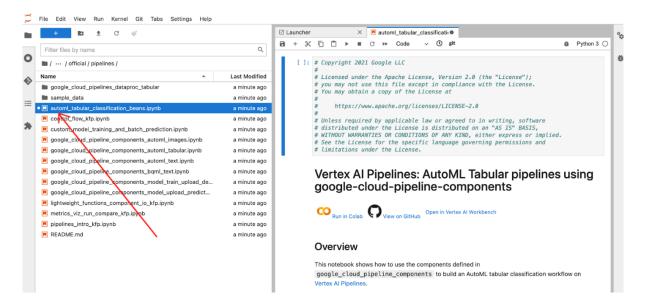
#### Set your project ID

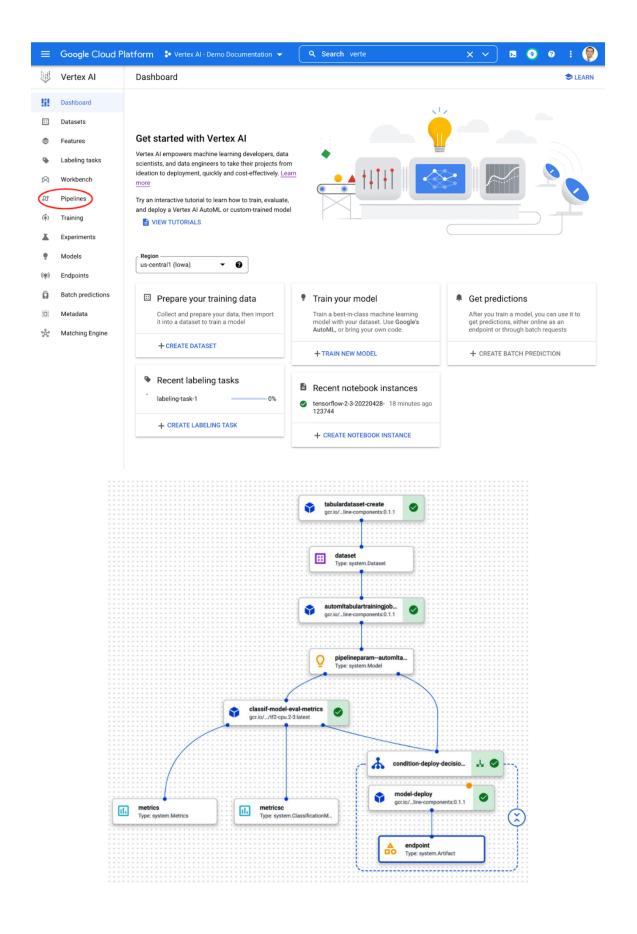
If you don't know your project ID, you may be able to get your project ID using gcloud.

[1]: import os
PROJECT\_ID = ""
# Get your Google Cloud project ID from gcloud
if not os.getenv("IS\_TESTING"):
 shell\_output = !gcloud config list --format 'value(core.project)' 2>/dev/null
PROJECT\_ID = shell\_output[0]
print("Project ID: ", PROJECT\_ID)
Project ID: vertex-ai-demo-documentation

Otherwise, set your project ID here.

[2]:	<pre>if PROJECT_ID == "" or PROJECT_ID is None:</pre>	
	<pre>PROJECT_ID = "python-docs-samples-tests"</pre>	<pre># @param {type:"string"}</pre>





### Artifact info

**VIEW LINEAGE** 

Name	dataset
Туре	system.Dataset
URI	aiplatform://v1/projects/462141068491/locations/
	us-central1/datasets/460712964224188416

#### Artifact info

VIEW LINEAGE	
Name	metricsc
Гуре	system.ClassificationMetrics
JRI	gs://sara-vertex-demos-bucket/pipeline_root/your-user-id/462141068491/automl-tab-beans- training-v2-20210611170830/classif-model-eval-metrics_6318374355340361728/metricsc

#### **Confusion matrix**

This table shows how often the model classified each label correctly (in blue), and which labels were most often confused for that label (in gray).

🔵 Item counts 🛨

	Predicted lat	bet baresunva	ant		JERMASON,	A	2	
True label	Predit	AARBC F	SOMBAY	7 <sup>11</sup> AL	JERIN.	HOROL	SERER C	IRA
BARBUNYA	94%	-	5%	_	_	1%	1%	
BOMBAY	_	100%	_	_	_	-	_	
CALI	2%	-	96%	-	1%	1%	1%	
DERMASON	_	-	_	94%	_	1%	6%	
HOROZ	_	-	_	1%	96%	-	3%	
SEKER	0%	-	_	1%	-	96%	3%	
SIRA	1%	-	_	9%	_	1%	90%	

←	automl-beans1623431305		II VIEW DATA SET	EXPORT	
EVAL	UATE	DEPLOY AND TEST	BATCH PREDICTIONS	MODEL PROPERTIES	

#### Deploy your model

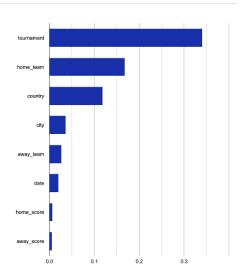
Endpoints are machine learning models made available for online prediction requests. Endpoints are useful for timely predictions from many users (for example, in response to an application request). You can also request batch predictions if you don't need immediate results.

DEPLO		OINT
DEPLO		

	Name	ID	Models	Region	Monitoring	Most recent monitoring job
0	automl- beans1623431305_endpoint	3328494376161640448	1	us- central1	Disabled	-

=	Google Cloud Platform	💲 Vertex Al - Demo D	ocumentation 👻	Q Search verte	× × <b>2</b> 0 :	9
Ų	Vertex AI	← women's for	otball resutls			1
il	Dashboard	SOURCE ANALY	ZE			
H	Datasets					>
9	Features	Dataset Info		Summary	Training jobs and models	
•	Labeling tasks	Created: Apr 28, 202 Dataset format: CSV	2.4:32 PM	Total columns: 9 Total rows: 4,314	women's football resutls (Version 1)	:
	Workbench	Dataset location(s): gs://demodocument/	/results.csv.[2]		Model type: Tabular	
N	Pipelines	ga.//demodocument/	-		TRAIN NEW MODEL	
(¢)	Training		Ge	neral statistics generated by Apr 28, 2022 4:42 PM GENERATE	STATISTICS	
¥	Experiments	<b>Filter</b> Enter pro			0	
•	Models	Column name	Missing % (count)	Distinct values	U	
(ę))	Endpoints	away_score	-	19		
ā	Batch predictions	away_team	-	184		
	Metadata	city	-	994		
0				144		
		country	-			
	Matching Engine	date	-	1824		
	Matching Engine	date home_score	-	1824 22		
ģ	Matching Engine	date	-	1824		

#### Feature Importance



### Deploy to endpoint

Model settings

Model monitoring

Monitoring objectives

DEPLOY CANCEL

I

#### Model monitoring supports AutoML tabular and custom-trained models and incurs additional charges, Learn more

Model monitoring

Menitoring job display name \* mm\_Women's football results\_2022429123532

#### 1\_Women's football results\_2022429123532

Montoring window length \* 24 The number of hours a monitoring job will run. After a job ends, a new job will start. Jacob and and an a good for endpoints with high prediction traffic, while a long window.

0

Model monitoring applies to all models deployed on this endpoint.
 Learn more

Models used in production require continuous monitoring to ensure that they perform as expected. Use model monitoring to track training-serving skew or prediction drift, then set up alerts to notify you when thresholds are crossed. Learn more

useru ro engoines with low preaction trainc, persuit window size is 24 hours. Alert emails \* fankhi khallov@ditoweb.com @ Enter one or more email addresses to receive an alert when a model exceeds an

Enter one or more email addresses to receive an alert when a model exceeds an alerting threshold

#### Sampling rate

#### Input schemas (optional)

Not required for AutoML models. Input schemas full Model Monitoring how to correctly parse the input payload. May be necessary for custom trained models that don't use a keyvalue input format. <u>Learn more</u>

 Prediction input schema
 BROWSE

VAML file that describes the format of a single prediction request instance. If not provided, Model Monitoring will try to parse the input schema automatically.

Analysis input schema
BROWSE

#### VAM, file that describes the format of a single prediction request that TensorFilo Validation analyses. If not provided, Model Monnoring will try to parse the input schema automatically.

#### Deploy to endpoint

- Oefine your endpoint
- Model settings
- Model monitoring

4 Monitoring objectives

DEPLOY CANCEL

#### Model monitoring applies to all models deployed on this endpoint 💡

#### Monitoring objective

0

#### O Training-serving skew detection

Training-serving skew occurs when the feature data distribution in production is different from the feature data distribution in model training

 Prediction drift detection
 Prediction drift occurs when feature data distribution in production changes significantly over time

#### Prediction drift detection

#### Alert thresholds (Optional)

Determines which features to monitor and distance between the input feature distribution and its baseline. At the end of each monitoring run, if any thresholds are crossed you'll receive an alert email. <u>Learn more</u>

If left blank, then all features are monitored and the alert threshold is .3.

Alert thresholds JSON



Train models that are configured to have attribution scores through Explainable AI

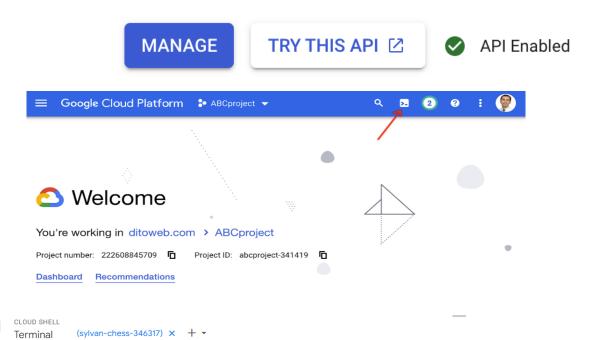
### **Appendix 5 - Practicing with Google Cloud ML API**



## **Cloud Vision API**

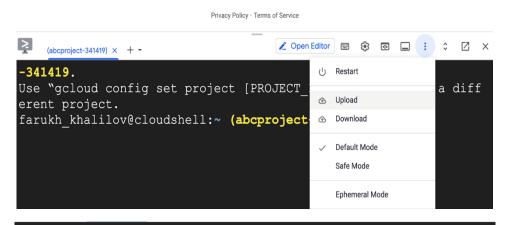
Google Enterprise API

Image Content Analysis



Welcome to Cloud Shell! Type "help" to get started. Your Cloud Platform project in this session is set to **sylvan-chess-346317**. Use "gcloud config set project [PROJECT\_ID]" to change to a different project. logan\_song@cloudshell:~ (sylvan-chess-346317)\$

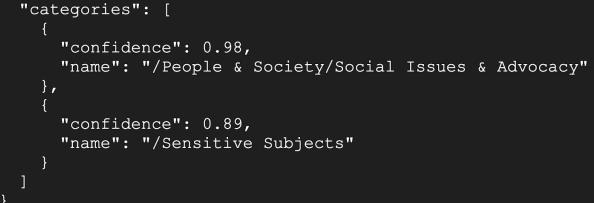












#### Google reviews



Local Guide · 14 reviews · 60 photos ★★★★ a month ago From the minute I walked into the door, the family atmosphere hit me like a wave. The people that manage this place of the highest quality and the food matches it. I had a stromboli which I usually avoid because they turn out gummy and nasty. This place was a complete opposite. The bite of fresh gaflic in the crust. The salty nutliness of the mozzarella, the quality of the pepperoni and thin sliced sausage. Everything deserves the chefs kiss. This restaurant is an hour and a half away from my home in Greenville but well worth it several times over. I will definitely be back.



Ragan & Holly's Pumpkin Patch Temporarily closed Trz2 Cloer Family-Vineyards SiteOne scape Supply.

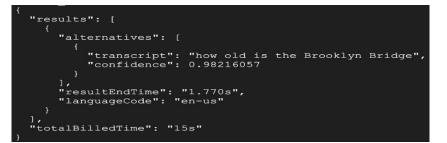
1 Like



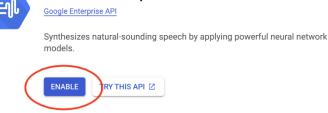




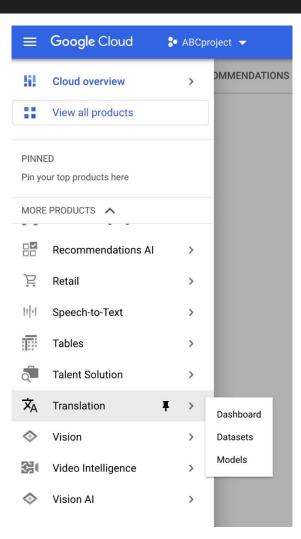


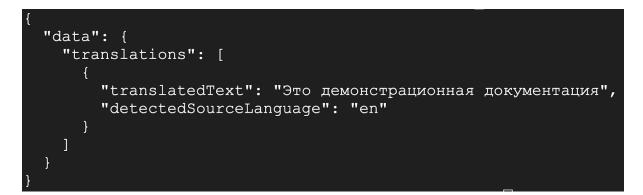


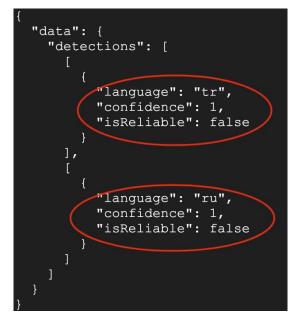
Cloud Text-to-Speech API



```
{
  "languageCodes": [
    "en-US"
 ],
  "name": "en-US-Standard-B",
  "ssmlGender": "MALE",
  "naturalSampleRateHertz": 24000
},
{
  "languageCodes": [
    "en-US"
 ],
  "name": "en-US-Standard-C",
  "ssmlGender": "FEMALE",
  "naturalSampleRateHertz": 24000
},
```







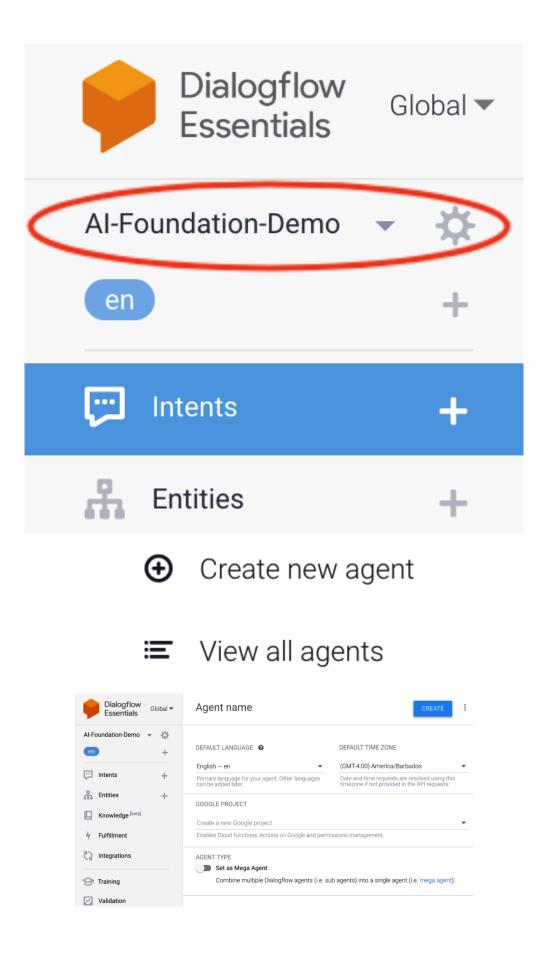


# **Dialogflow API**

Google Enterprise API

Builds conversational interfaces

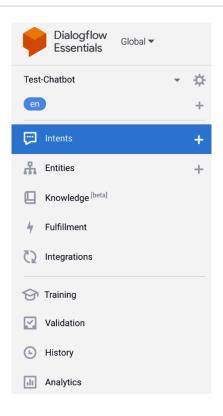




DEFAULT LANGUAGE	DEFAULT TIME ZONE
English — en 🔹	(GMT-4:00) America/Barbados
Primary language for your agent. Other languages can be added later.	Date and time requests are resolved using this timezone if not provided in the API requests.
GOOGLE PROJECT	
Create a new Google project	
Enables Cloud functions, Actions on Google and perm	issions management.

#### Set as Mega Agent

Combine multiple Dialogflow agents (i.e. sub agents) into a single agent (i.e. mega agent).



#### ✤ Fulfillment

#### Webhook

Your web service will receive a POST request from Dialogflow in the form of the response to a user query matched by intents with webhook enable

#### Inline Editor (Powered by Google Cloud Functions)

Build and manage fulfillment directly in Dialogflow via Cloud Functions. Docs

() Newly created cloud functions now use Node.js 10 as runtime engine. Check migration guide for more details.

inde	x.js package.json
1	// See https://github.com/dialogflow/dialogflow-fulfillment-nodejs
2	// for Dialogflow fulfillment library docs, samples, and to report issues
3	'use strict';
4	
5	<pre>const functions = require('firebase-functions');</pre>
6	<pre>const {WebhookClient} = require('dialogflow-fulfillment');</pre>
7	<pre>const {Card, Suggestion} = require('dialogflow-fulfillment');</pre>
8	
9	<pre>process.env.DEBUG = 'dialogflow:debug'; // enables lib debugging statements</pre>
10	
11	<pre>exports.dialogflowFirebaseFulfillment = functions.https.onRequest((request, response) =&gt; {</pre>
12	<pre>const agent = new WebhookClient({ request, response });</pre>
13	<pre>console.log('Dialogflow Request headers: ' + JSON.stringify(request.headers));</pre>
14	console.log('Dialogflow Request body: ' + JSON.stringify(request.body));
15	

🖵 Intents

CREATE INTENT



#### Responses 🔞

DEFAULT 🕂

Text Response					
1	Hi! How are you doing?				
2	Hello! How can I help you?				
3	Good day! What can I do for you today?				
4	Greetings! How can I assist?				
5	Enter a text response variant				
ADD	ADD RESPONSES				
	Set this intent as end of conversation				

#### Responses 🕜

Тех	t Response
1	I didn't get that. Can you say it again?
2	I missed what you said. What was that?
3	Sorry, could you say that again?
4	Sorry, can you say that again?
5	Can you say that again?
6	Sorry, I didn't get that. Can you rephrase?
7	Sorry, what was that?
8	One more time?
9	What was that?
10	Say that one more time?
11	I didn't get that. Can you repeat?
12	I missed that, say that again?
13	Enter a text response variant

### 🖵 Intents . Q **T** Search intents Default Fallback Intent Default Welcome Intent opening\_times 000 Contexts 🚱 $\sim$ Events 🕜 $\sim$ Training phrases 🔞 $\overline{}$



#### Train the intent with what your users will say

Provide examples of how users will express their intent in natural language. Adding numerous phrases with different variations and parameters will improve the accuracy of intent matching. Learn more

ADD TRAINING PHRASES

99	Add user expression
99	Are you open every day?
99	When are you open?
<b>77</b>	Opening times
<b>9</b> 7	What are your opening times?

### Responses 😮



### Execute and respond to the user

Respond to your users with a simple message, or build custom rich messages for the integrations you support. Learn more

#### **ADD RESPONSE**

Resp	Responses 🕜			
DEFAU	ur +			
Tex	t Response	0 Ū		
1	We are open every day from 9:00 am to 5:00 pm			
2	Enter a text response variant			
ADD RESPONSES				
	Set this intent as end of conversation 🛛 🔞			

Try it now	Ŷ
Agent	
USER SAYS when open?	COPY CURL
DEFAULT RESPONSE We are open every day from	• n 9:00 am to 5:00 pm
CONTEXTSsystem_counters	RESET CONTEXTS
INTENT opening_times	
ACTION Not available	
SENTIMENT Query Score: -0.2	
DIAGNOSTI	C INFO

### **99** Add user expression

<b>99</b>	May I have a pizza?
<b>99</b>	Can I have a pizza?
<b>99</b>	l want a pizza.
<b>99</b>	Can I order a pizza?

 $\boldsymbol{\wedge}$ 

### Responses 🔞

### DEFAULT +

Tex	t Response	01
1	Sure. You can get a pizza.	
2	Enter a text response variant	

### ADD RESPONSES

### USER SAYS

### COPY CURL

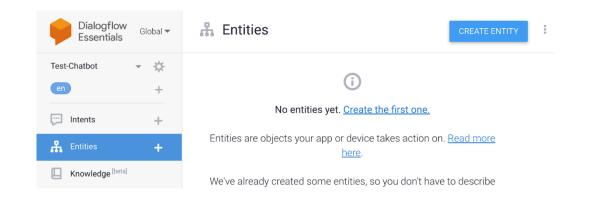
### I want a slice of pizza

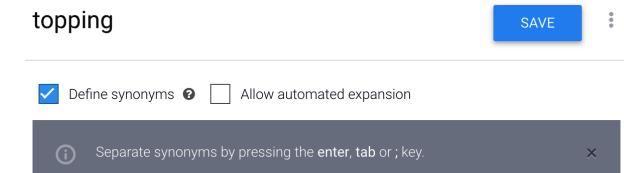


Sure. You can get a pizza.

### INTENT

order\_pizza





cheese	cheese		
veggie	veggie	vegetarian	Enter synonym
pineapple	pineapple		
beef	beef		
ham	ham		

<b>77</b>	I want <mark>two</mark> pizzas. <mark>One</mark> is veggie and one is cheese.
<b>5</b> 5	Can I have a pizza with bacon and pinapple
<b>7</b> 7	I want to order cheese pizza
<b>99</b>	May I have a pizza?
<b>7</b> 7	Can I have a pizza?
<b>99</b>	l want a pizza.
<b>7</b> 7	Can I order a pizza?

99 I want <mark>tw</mark>	<mark>/o</mark> pizzas. <mark>(</mark>	<mark>)ne</mark> is veggie and	one is chee	ese.	
PARAMETER N	JAME	ENTITY		RESOLVED VALUE	E
number		<mark>@sys.number</mark>		two	×
number1		@sys.number		One	×
•	English (en)	@sys.cardinal	ten	10	
	English (en)	@sys.ordinal	tenth	10	
	English (en)	@sys.number-integer	12	12	
	English (en)	@sys.number-sequence	1 2 2003	123	
	English (en)	@sys.flight-number	LH4234	LH 4234	
	English (en)	@sys.unit-area	ten square feet	{"amount":10,"unit":"sq ft"}	
	English (en)	@sys.unit-currency	5 dollars 25 pounds	{"amount":5,"currency":"USD"} {"amount":25,"currency":"GBP" }	
	English (en)	@sys.unit-length	ten meters	{"amount":10,"unit":"m"}	
<b>99</b> I want <mark>tw</mark> PARAMETER N		O <mark>ne</mark> is veggie and o ENTITY	one is chees	se. topping	
number		<mark>@sys.nu</mark>	Imber	@topping	
number1		@sys.nu	imber		+ Create new

99 I want <mark>two</mark> pizzas. Or	ne is veggie and one is <mark>chees</mark> e	2.	
99 Can I have a pizza wi	th <mark>bacon</mark> and <mark>pinapple</mark>		
PARAMETER NAME	ENTITY	RESOLVED VALUE	
topping	@topping	bacon	×
topping1	@topping	pinapple	×
I want to order chees	e pizza		
May I have a pizza?			
Can I have a pizza?			
99 I want a pizza.			
Can I order a pizza?			

### Action and parameters

Enter action na	me			1.
REQUIRED 😧	PARAMETER NAME	ENTITY 😧	VALUE	IS LIST
	number	@sys.number	\$number	
	topping	@topping	\$topping	
	Enter name	Enter entity	Enter value	

ゝ

~

#### Responses 🕜

DEFAULT +

Tex	t Response	Ô
1	Sure. You can get a pizza with \$topping	
2	Enter a text response variant	

### Can I have a cheese pizza?





### Sure. You can get a pizza with cheese

### INTENT

order\_pizza

Action and par	rameters					^
Enter action na	me					1.
REQUIRED 🚱	PARAMETER NAME 🕝	ENTITY 🕑	VALUE	IS LIST	PROMPTS 🛛	
	number	@sys.num ber	\$number		_	
	topping	@topping	\$topping	<b>~</b>	Define pro mpts	
	Enter nam	Enter entit	Enter		_	

#### Prompts for "topping"

NA	AME	ENTITY	VALUE
topping @topping		@topping	\$topping
	PROMPTS		
1	What toppings do you wa	ant on your pizza?	

CLOSE

I want a pizza



• 0	rder_pizza.upsell_pizza - yes	:
99	why not	
99	yes that's alright	
55	yes I do	
55	exactly	
55	of course	
55	yep that's ok	
99	okay	
55	ok	
	1 0F 5 →	

der_pizza.ord	ler_pizza-yes			
REQUIRED 0	PARAMETER NAME	ENTITY 🕑	VALUE	IS LIST
	Enter name	Enter entity	Enter value	

Resp	esponses 🕜	
DEFAU	ит <b>+</b>	
Tex	rt Response	Ô
1	Great! What topping do you want on your pizza?	
2	Enter a text response variant	
ADD	DRESPONSES	

Set this intent as end of conversation 3

o	rder_pizza.upsell_pizza - no
"	no
<b>99</b>	no no don't
<b>9</b> 9	na
<b>9</b> 9	no it isn't
<b>99</b>	don't
<b>5</b> 5	nah I'm good
<b>9</b> 9	no I cannot
"	Ican't
	1 OF 5 →

Action and parameters				
order_pizza.o	order_pizza-no			ĥ
REQUIRED	PARAMETER NAME	ENTITY 🚱	VALUE	IS LIST
	Enter name	Enter entity	Enter value	
+ New paramet	er			
Responses 🛛				^
DEFAULT +				

Tex	t Response	Ô
1	Ok. Do you want a drink to go with it?	
2	Enter a text response variant	