Business Analytics, Geo Analytics and Machine Learning with BigQuery

Alex Urcola
Kschool
Clase 1/2

¿Quién soy? : Alex Urcola

Alex Urcola
Senior Business Analytics Consultant
Google Spain

Administración y Dirección de Empresas
Deusto

Master en finanzas y Contabilidad
ICADE

Master en Big Data y Business Intelligence
MSMK

Master en Data Science
Kschool

Senior financial auditor
PwC

Business Analytics Consultant
Google Spain

Agenda

01 Introduccion a BigQuery

02 Conceptos básicos de Standard SQL

Break (🎉🎉)

03 DataStudio como herramienta de Visualización

04 Ejercicio práctico BigQuery y DataStudio

05 BigQuery GeoViz

Fin (🎉🎉)

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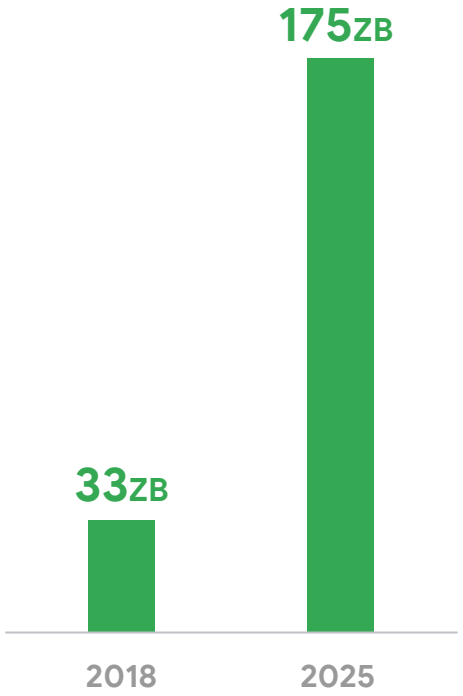
Fin (🎉🎉)

Traditional data warehouses are melting with data growth

World datasphere will grow from
33 ZB in 2018
to 175 ZB by 2025 -IDC*



https://www.seagate.com/files/www-content/our-story/trends/files/idc-seagate-dataage-whitepaper.pdf

Is your data warehouse ready for real-time data ?

"By 2025, more than a quarter of data created in the global datasphere will be real time in nature."

IDC

Google BigQuery

Google Cloud Platform's **enterprise data warehouse** for analytics

Gigabyte- to **petabyte-scale** storage and SQL queries

Encrypted, durable,
And highly available

GeoVizualizations
And geometric operations

Unique

Real-time insights from streaming data

Unique

Built-in **ML and GIS** for out-of-the-box predictive insights

Unique

High-speed, in-memory **BI Engine** for faster reporting and analysis

Unique

BigQuery | Why is so powerful

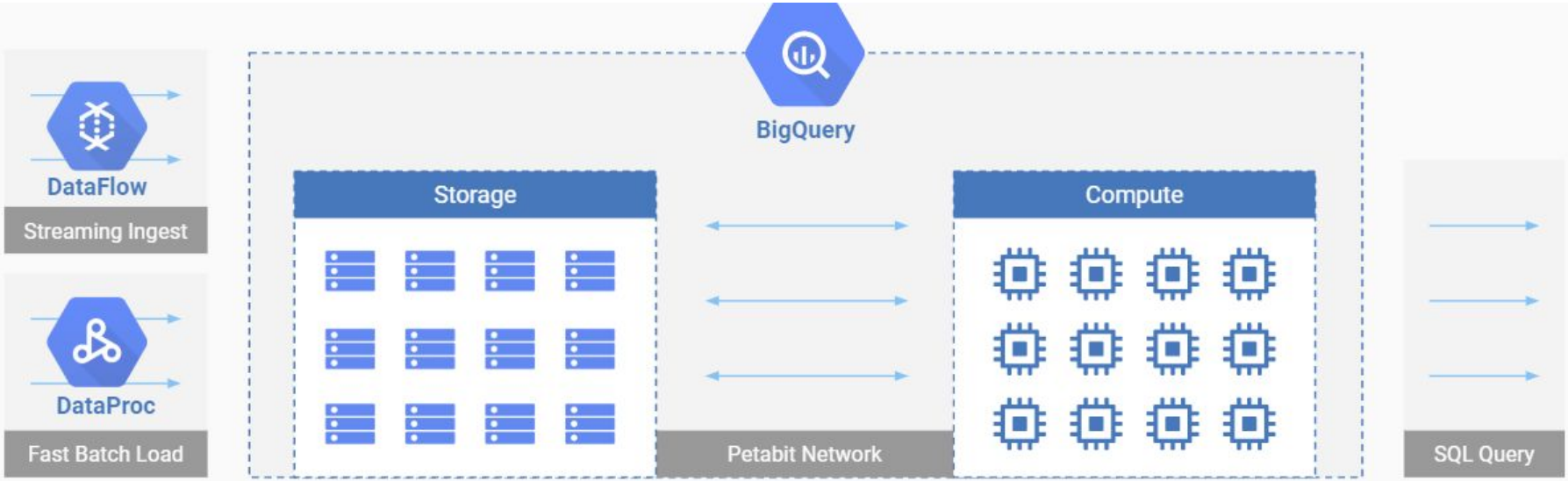
1. **Storage Differentiated from compute:** Permanent Storage Vs Temporal compute makes cheaper and faster

2. **Columnar Based storage:** Data model is based on columns vs registers making faster and cheaper

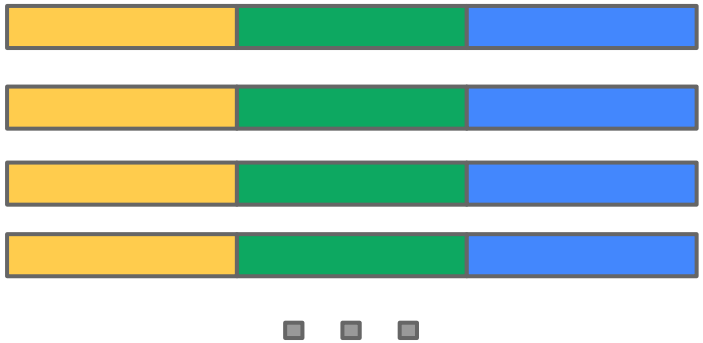
3. **Serverless:** Data model is based on columns vs registers making faster and cheaper

BigQuery | Storage Vs Compute

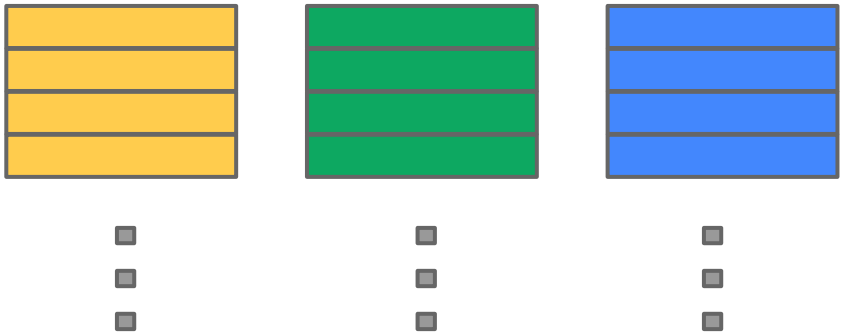
BigQuery = **Massively Parallel Processing** query with the petabit network and thousands of servers



BigQuery | Columnar based storage



Record-Oriented Storage



Column-Oriented Storage

BigQuery | Columnar based storage - Example

Table Definition

```
message Book {
 required string title,
 repeated string author,
 repeated group price {
   optional int64 discount,
   optional int64 usd,
   optional int64 eur,
 }
}
```

Field Records

```
Book1:
 author: "AAA"
 title: "firstTitle"
 price:
  discount: 0
  eur: 11
  usd: 12

Book2:
 author: "BBB"
 author: "CCC"
 author: "DDD"
 title: "secondTitle"

Book3:
 title: "thirdTitle"
 price:
  discount: 0
  eur: 11
 price:
  discount: 1
  eur: 11
```

BigQuery | Columnar based storage - Example

R & D Definition

```
Book1:
 author: "AAA"              R: 0, D: 1
 title: "firstTitle"        R: 0, D: 1
 price:
  discount: 0               R: 0, D: 2
  eur: 11                   R: 0, D: 2
  usd: 12                   R: 0, D: 2

Book2:
 author: "BBB"              R: 0, D: 1
 author: "CCC"              R: 1, D: 1
 author: "DDD"              R: 1, D: 1
 title: "secondTitle"       R: 0, D: 1
 (price):
  (discount: null)          R: 0, D: 0
  (eur: null)               R: 0, D: 0
  (usd: null)               R: 0, D: 0

Book3:
 title: "thirdTitle"        R: 0, D: 1
 (author: null)             R: 0, D: 0
 price:
  discount: 0               R: 0, D: 2
  eur: 11                   R: 0, D: 2
  (usd: null)               R: 0, D: 1
 price:
  discount: 1               R: 1, D: 2
  eur: 11                   R: 1, D: 2
  (usd: null)               R: 1, D: 1
```

Price.Eur column storage

```
compressed value, R, D

11 R: 0, D: 2
NULL R: 0, D: 0
11 R: 0, D: 2
11 R: 1, D: 2
```

BigQuery | Columnar based storage

Value: Stored Value
Repetition (r) the level of the nesting in the field path at which the repetition is happening
Definition (d) how many optional/repeated fields in the field path have been defined.

```
DocId: 10                    r1
Links
  Forward: 20
  Forward: 40
  Forward: 60
Name
  Language
    Code: 'en-us'
    Country: 'us'
  Language
    Code: 'en'
  Url: 'http://A'
Name
  Url: 'http://B'
Name
  Language
    Code: 'en-gb'
    Country: 'gb'
```

```
message Document {
  required int64 DocId;
  optional group Links {
    repeated int64 Backward;
    repeated int64 Forward; }
  repeated group Name {
    repeated group Language {
      required string Code;
      optional string Country; }
    optional string Url; }}
```

```
DocId: 20                    r2
Links
  Backward: 10
  Backward: 30
  Forward: 80
Name
  Url: 'http://C'
```

DocId

value	r	d
10	0	0
20	0	0

Name.Url

value	r	d
http://A	0	2
http://B	1	2
NULL	1	1
http://C	0	2

Links.Forward

value	r	d
20	0	2
40	1	2
60	1	2
80	0	2

Links.Backward

value	r	d
NULL	0	1
10	0	2
30	1	2

Name.Language.Code

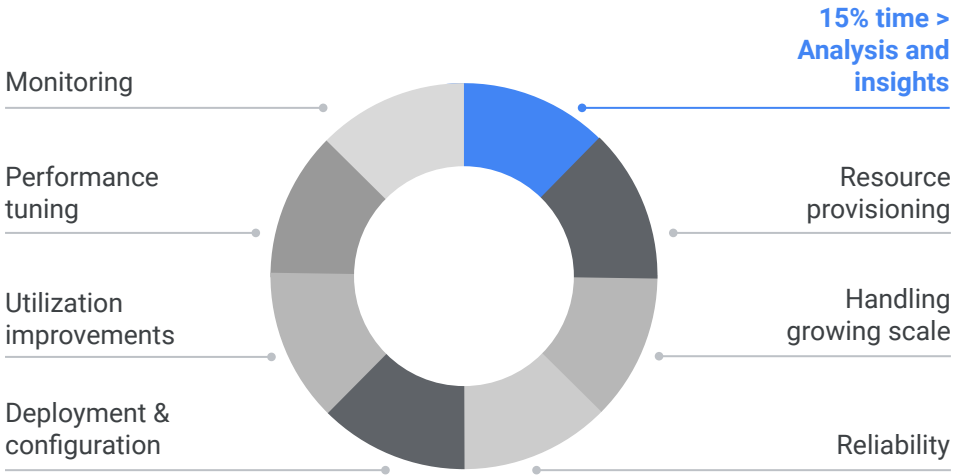
value	r	d
en-us	0	2
en	2	2
NULL	1	1
en-gb	1	2
NULL	0	1

Name.Language.Country

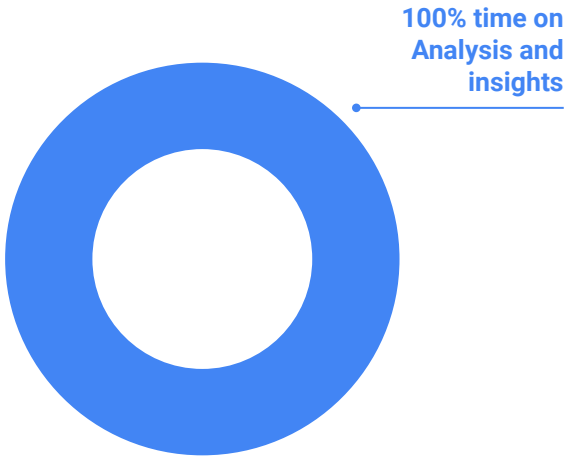
value	r	d
us	0	3
NULL	2	2
NULL	1	1
gb	1	3
NULL	0	1

BigQuery | Serverless data warehouse

Traditional data warehouses

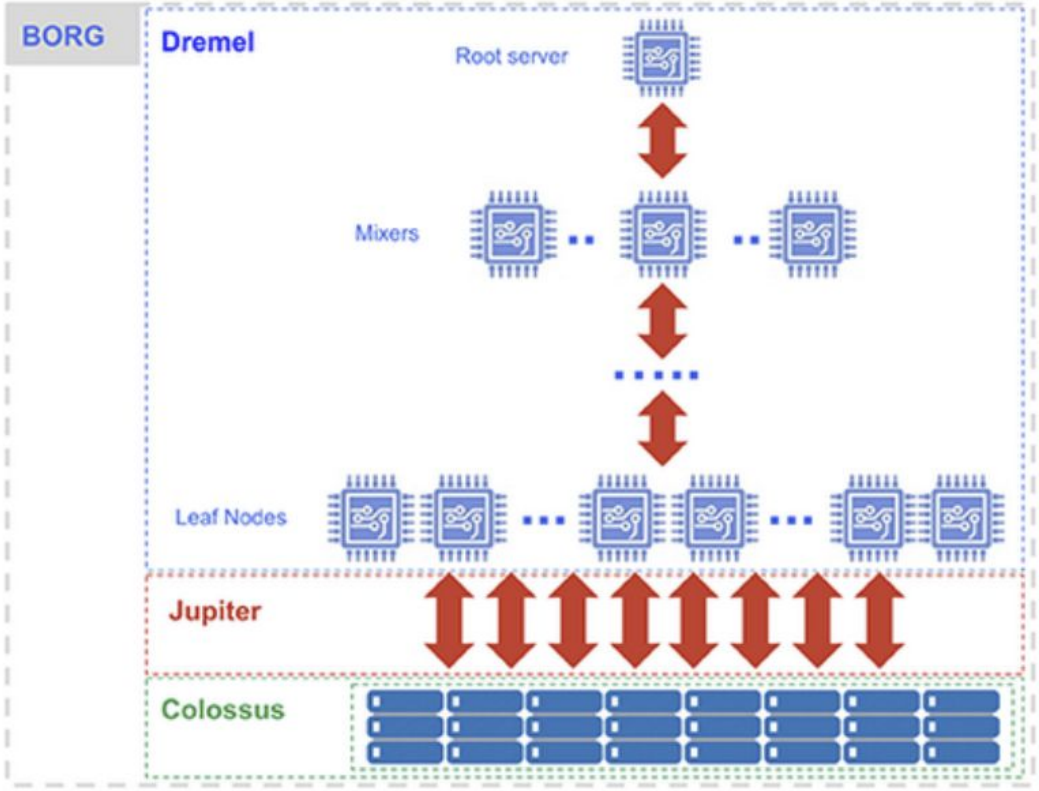


BigQuery's serverless analytics

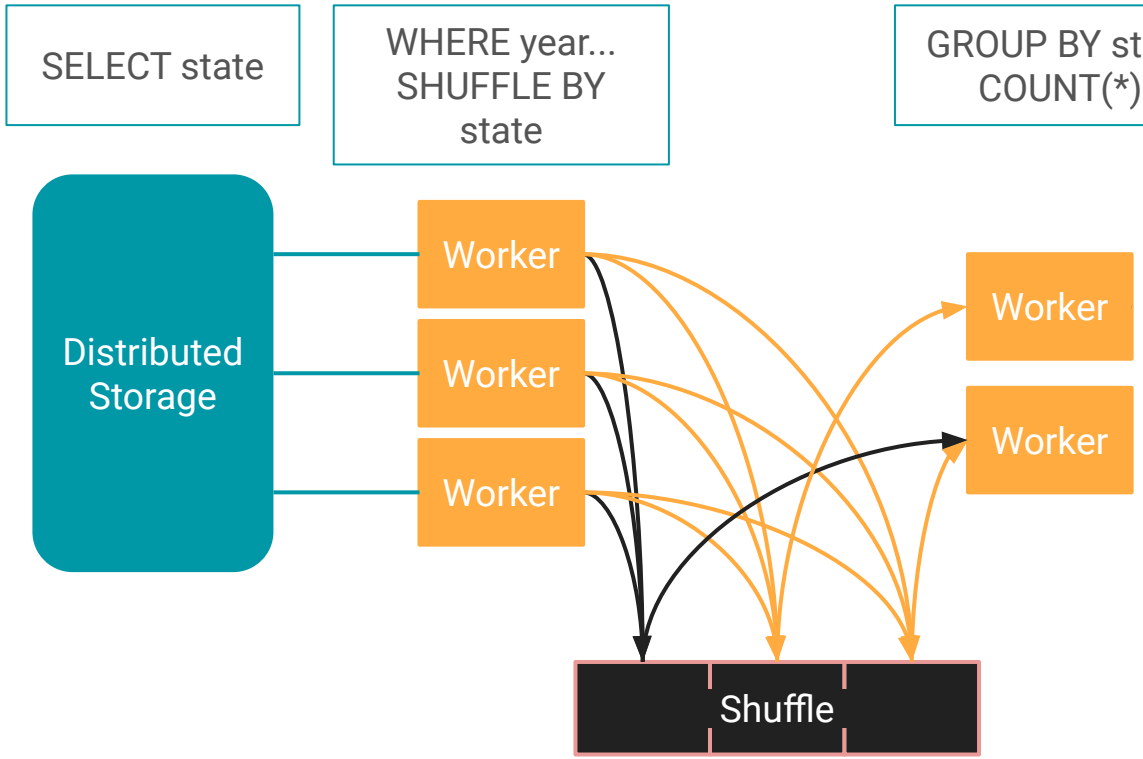


BigQuery | Serverless data warehouse - Example

- Workers responsible for aggregations
- Network to Move Data leaf nodes to mixers
- Workers that read and compute
- Network to Move Data from Colossus to workers
- Distributed Columnar Storage System



BigQuery | Serverless data warehouse - Example



Shuffle does not block future stages

BigQuery uses dynamic partitioning to distribute shuffle optimally

Substantial key-skew can still impact performance

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Fin (🎉🎉)

Standard SQL | Query Basics

SELECT FROM

```
SELECT column
FROM `project.dataset.table`
```

SELECT FROM

```
select origin from
`chrome-ux-report.country_es.201907`
```

Add limit clause to limit results

```
select origin from
`chrome-ux-report.country_es.201907` limit 10
```

Add order by clause to sort results

```
select origin from
`chrome-ux-report.country_es.201907` order by
origin desc limit 10
```

Standard SQL | Query Basics

Filter using Where clause

```
select origin from
`chrome-ux-report.country_es.201907`
where regexp_contains(origin,'bbva')
order by origin desc limit 10
```

Cast Functions (link) to change date type

```
select cast(fare as string) as castedfare from `bigquery-public-data.chicago_taxi_trips.taxi_trips` limit 10
```

Standard SQL | Intro to Functions

Date Functions (link)

SELECT CURRENT_DATE() as the_date; ⟶ Current Date
SELECT EXTRACT(WEEK from CURRENT_DATE()) as the_date_day; ⟶ Extract Week
SELECT EXTRACT(WEEK(SUNDAY) from CURRENT_DATE()) as the_date_day; ⟶ Extract Week starting on sunday
SELECT
date(trip_start_timestamp,"Europe/Madrid") as date
from `bigquery-public-data.chicago_taxi_trips.taxi_trips` -->Extract date from a timestamp
SELECT DATE_ADD(CURRENT_DATE(), INTERVAL 5 DAY) as five_days_later; ⟶ Add dates
SELECT DATE_SUB(CURRENT_DATE(), INTERVAL 5 DAY) as five_days_ago; ⟶ substract dates
SELECT DATE_DIFF('2017-12-30', '2014-12-30', YEAR) AS year_diff;
SELECT DATE_DIFF('2017-12-30', '2014-12-30', DAY) AS day_diff;
SELECT PARSE_DATE("%x", "12/25/08") as parsed; ⟶ parse date 2008-12-25
SELECT FORMAT_DATE("%x", DATE "2008-12-25") as US_format; ⟶ parse_date 12/25/08
SELECT DATE_TRUNC(DATE '2008-12-25', month) as start_of_month;
SELECT TIMESTAMP_MILLIS(1230219000000) as timestamp; ⟶ change miliseconds to timestamp

Standard SQL | Intro to Functions

String Functions (link)

SELECT cast(CONCAT('1','2') as float64) as concated;; → Concatenate string and convert to float

SELECT lower("APPLE") as lowered; → Lower capital letters

Standard SQL | Intro to Functions

Aggregation Functions (link)

```
SELECT sum(totrevenue) as revenue ,
    avg(totrevenue) as avg_revenue ,
    round(avg(totrevenue),2) as avg_revenue_round ,
    count(ein) as nonprofits,
    count(distinct ein) as nonprofitsdistinct,
    count(*) as total
    from `bigquery-public-data.irs_990.irs_990_2016`;
```

Standard SQL | Intro to Functions

Aggregation grouping Functions (link)

```
SELECT
ein as nonprofit,
sum(totrevenue) as revenue ,
    round(avg(totrevenue),2) as avg_revenue_round ,
    count(ein) as nonprofits,
    count(distinct ein) as nonprofitsdistinct,
    count(*) as total
    from `bigquery-public-data.irs_990.irs_990_2016`
Group by ein;
```

Standard SQL | Intro to Functions

Statistical Functions (link)

```
SELECT
stddev(noemplyeesw3cnt) as st_dev_employee_count,
avg(noemplyeesw3cnt) as avg_employee_count,
APPROX_QUANTILES(noemplyeesw3cnt, 100)[OFFSET(99)] AS employee_count_percentile_99,
APPROX_QUANTILES(noemplyeesw3cnt, 100)[OFFSET(90)] AS employee_count_percentile_90,
APPROX_QUANTILES(noemplyeesw3cnt, 100)[OFFSET(70)] AS employee_count_percentile_70,
APPROX_QUANTILES(noemplyeesw3cnt, 100)[OFFSET(50)] AS employee_count_percentile_50,
corr( totprgmrevnue, totfuncexpns) as corr_rev_expense,
approx_count_distinct(ein) as approx_nonprofits,
count(distinct ein) as nonprofits
    from `bigquery-public-data.irs_990.irs_990_2016`
```

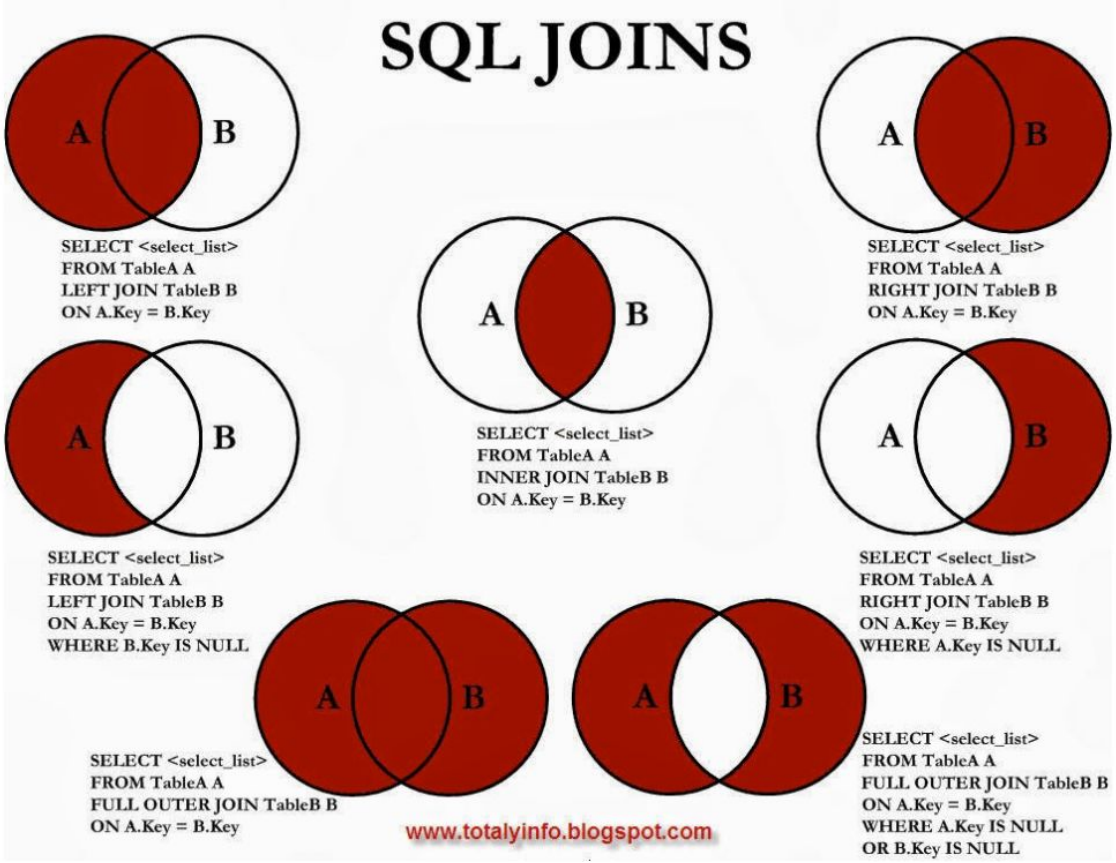
Standard SQL | Intro to Joins

Joins (link)

```
SELECT
t1.ein as ein,
t1.noemplyeesw3cnt as nom_of_employees,
t2.state as state

    from `bigquery-public-data.irs_990.irs_990_2016` as t1
     INNER JOIN
`bigquery-public-data.irs_990.irs_990_ein`as t2
    USING(ein)
```

Standard SQL | Intro to Joins



Standard SQL | Intro to temporary tables

Temporary tables (link)

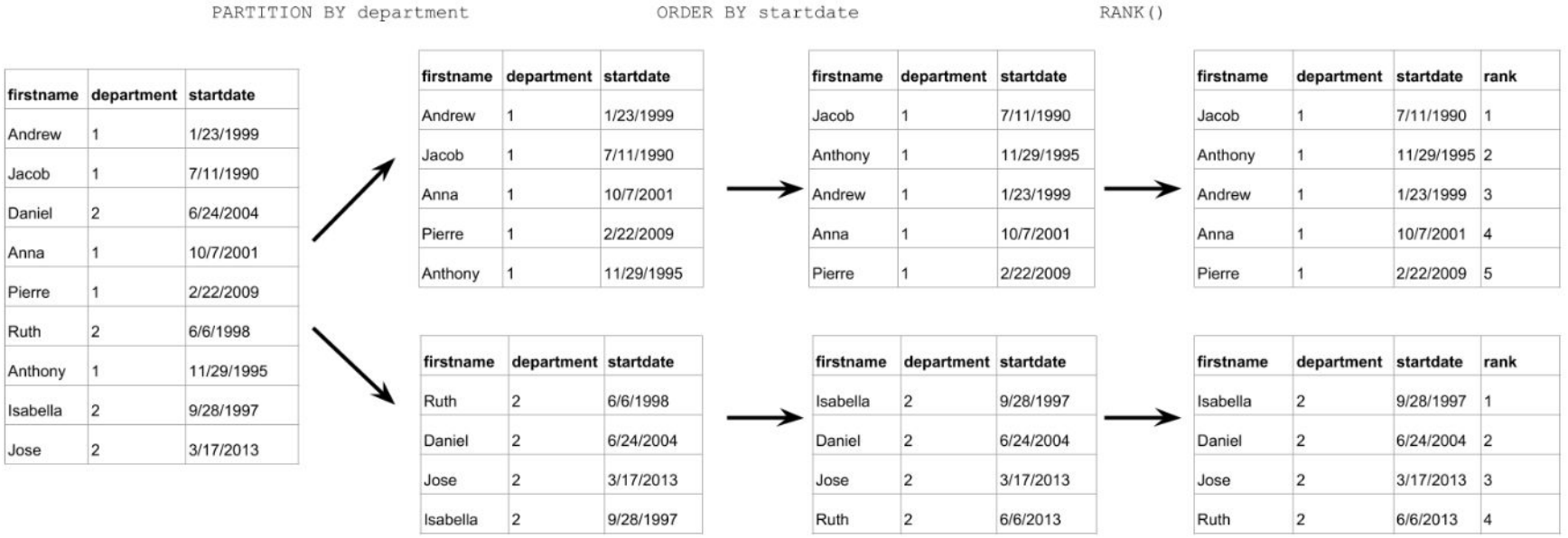
```
with WY_state as (select ein as filter from
`bigquery-public-data.irs_990.irs_990_ein` where state = "WY")
select
ein as ein,
noemplyeesw3cnt as nom_of_employees

    from `bigquery-public-data.irs_990.irs_990_2016`

    where ein in (select filter from WY_state)
```

Standard SQL | Intro to Functions

Analytical Functions - Rank (link)



firstname	department	startdate
Andrew	1	1/23/1999
Jacob	1	7/11/1990
Daniel	2	6/24/2004
Anna	1	10/7/2001
Pierre	1	2/22/2009
Ruth	2	6/6/1998
Anthony	1	11/29/1995
Isabella	2	9/28/1997
Jose	2	3/17/2013

firstname	department	startdate
Andrew	1	1/23/1999
Jacob	1	7/11/1990
Anna	1	10/7/2001
Pierre	1	2/22/2009
Anthony	1	11/29/1995

firstname	department	startdate
Jacob	1	7/11/1990
Anthony	1	11/29/1995
Andrew	1	1/23/1999
Anna	1	10/7/2001
Pierre	1	2/22/2009

firstname	department	startdate	rank
Jacob	1	7/11/1990	1
Anthony	1	11/29/1995	2
Andrew	1	1/23/1999	3
Anna	1	10/7/2001	4
Pierre	1	2/22/2009	5

firstname	department	startdate
Ruth	2	6/6/1998
Daniel	2	6/24/2004
Jose	2	3/17/2013
Isabella	2	9/28/1997

firstname	department	startdate
Isabella	2	9/28/1997
Daniel	2	6/24/2004
Jose	2	3/17/2013
Ruth	2	6/6/2013

firstname	department	startdate	rank
Isabella	2	9/28/1997	1
Daniel	2	6/24/2004	2
Jose	2	3/17/2013	3
Ruth	2	6/6/2013	4

Standard SQL | Intro to Functions

Analytical Functions - Rank (link)

```
SELECT firstname, department, startdate,
  RANK() OVER ( PARTITION BY department ORDER
BY startdate ) AS rank
FROM Employees;
```

Standard SQL | Intro to Functions

Analytical Functions - Rank (link)

```
with ranked as (

SELECT
t1.ein as ein,
t2.name as name,
t1.noemplyeesw3cnt as nom_of_employees,
t2.state as state,
rank() over (partition by state order by t1.noemplyeesw3cnt desc) as rank
    from `bigquery-public-data.irs_990.irs_990_2015` as t1
     INNER JOIN `bigquery-public-data.irs_990.irs_990_ein`as t2
    USING(ein)
    group by 1,2,3,4
    )

    select * from ranked where rank = 1
    order by nom_of_employees desc
```

Standard SQL | Arrays & structs

Arrays (link)

Arrays are **ordered lists** of zero or more data values that must have the **same data type**

Standard SQL | Arrays & structs

Arrays (link)

select ['a','b','c'] as array_sample

Row	array_sample
1	a
	b
	c

with sample as (select ['a','b','c'] as array_sample)
select array_length(array_sample) as array_sample_length from sample

Row	array_sample_length
1	3

select ['a','b','c'] as array_sample, 'field' as field → BigQuery Creates Nested Field Structres

Results | Details

Row	array_sample	field
1	a	field
	b	
	c	

Standard SQL | Arrays & structs

Unnest (link)

```
select array_sample,field from
nested_table,unnest(array_sample) as array_sample
```

Row	array_sample	field
1	a	field
2	b	field
3	c	field

Create array (link)

```
with table as (select 'a' as field union all select 'b' as field union all
select 'c' as field)

select array_agg(field order by field desc) as array_created from
table
```

Row	array_created
1	a
	b
	c

Standard SQL | Arrays & structs

Structs (link)

STRUCT are a container of ordered fields each with a type (required) and field name (optional).

You can store multiple data types in a STRUCT (even Arrays!)

Standard SQL | Arrays & structs

Structs (link)

```
select struct(35 as age, ['alicia','pedro'] as names) as info
```

Row	info.age	info.names
1	35	alicia
		pedro

```
select struct(35 as age, 'pedro' as names, ['p1','p2','p3'] as products) as info
```

Row	info.age	info.names	info.products
1	35	pedro	p1
			p2
			p3

Arrays of Structs:

```
select

[struct(35 as age, 'pedro' as names, ['p1','p2','p3'] as products),
struct(30 as age, 'maria' as names, ['p1','p6','p8'] as products)] as info
```

Row	info.age	info.names	info.products
1	35	pedro	p1
			p2
			p3
	30	maria	p1
			p6
			p8

Standard SQL | Arrays & structs

Arrays & Structs - filter customers that bought p1 (link)

```
with table as (

select

[struct(35 as age, 'pedro' as names, ['p1','p2','p3'] as products),
struct(30 as age, 'maria' as names, ['p1','p6','p8'] as products),
struct(37 as age, 'juan' as names, ['p2','p7','p9'] as products)
] as info)
select
names
from table
, unnest(info) as info
where 'p1' in unnest(info.products)
```

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Fin (🎉🎉)

Data Studio: Google's first* BI/Reporting tool available externally

Connect to all your data

Visualize with beautiful, informative reports

Share across the organization and around the world

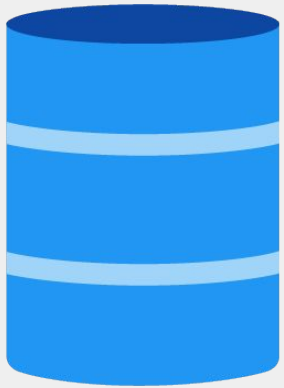
*Google just acquired Looker, but will continue to invest in Data Studio.

Why Data Studio?

Data Studio provides tools to create **beautiful reports** & perform **powerful ad-hoc analysis**.

PROS	CONS
• Large number of data connectors • Easy to maintain • New solution(ish) - constantly developed • Easy to use • Tech skills not mandatory • Easy sharing and collaboration • Free & globally available	• New(ish) solution - constantly developed • Limited formal support • (Somewhat) limited ability to customise (vs. other tools like Tableau)

Data entity relationship

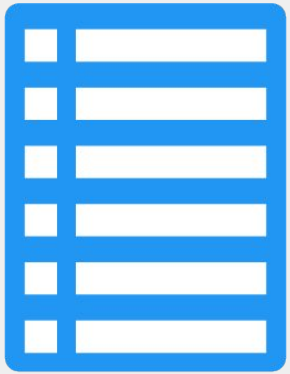


Data set

Exists outside
Data Studio

Data
connector

Exists inside
Data Studio



Data source

Exists inside
Data Studio

Report

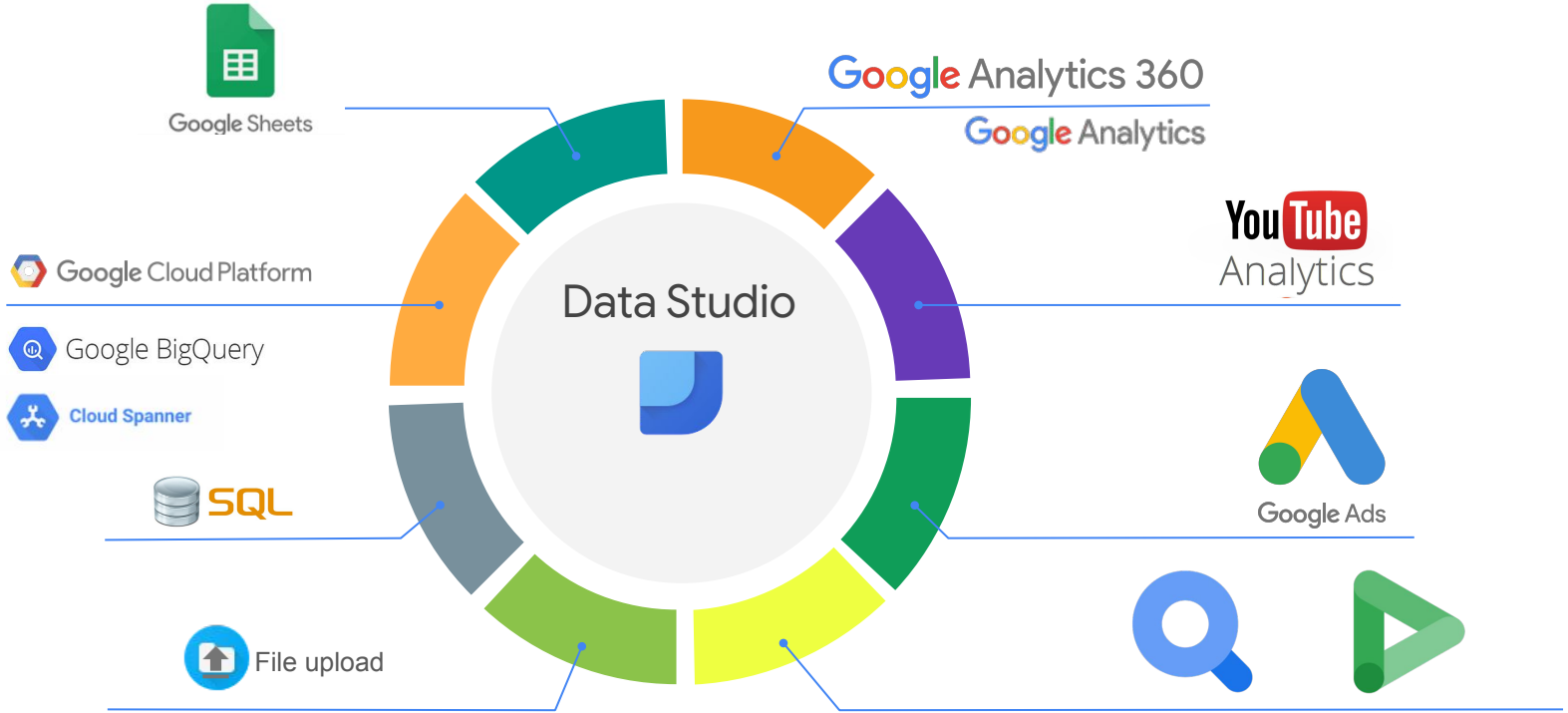
Exists inside
Data STudio

Data sources connect to underlying data sets

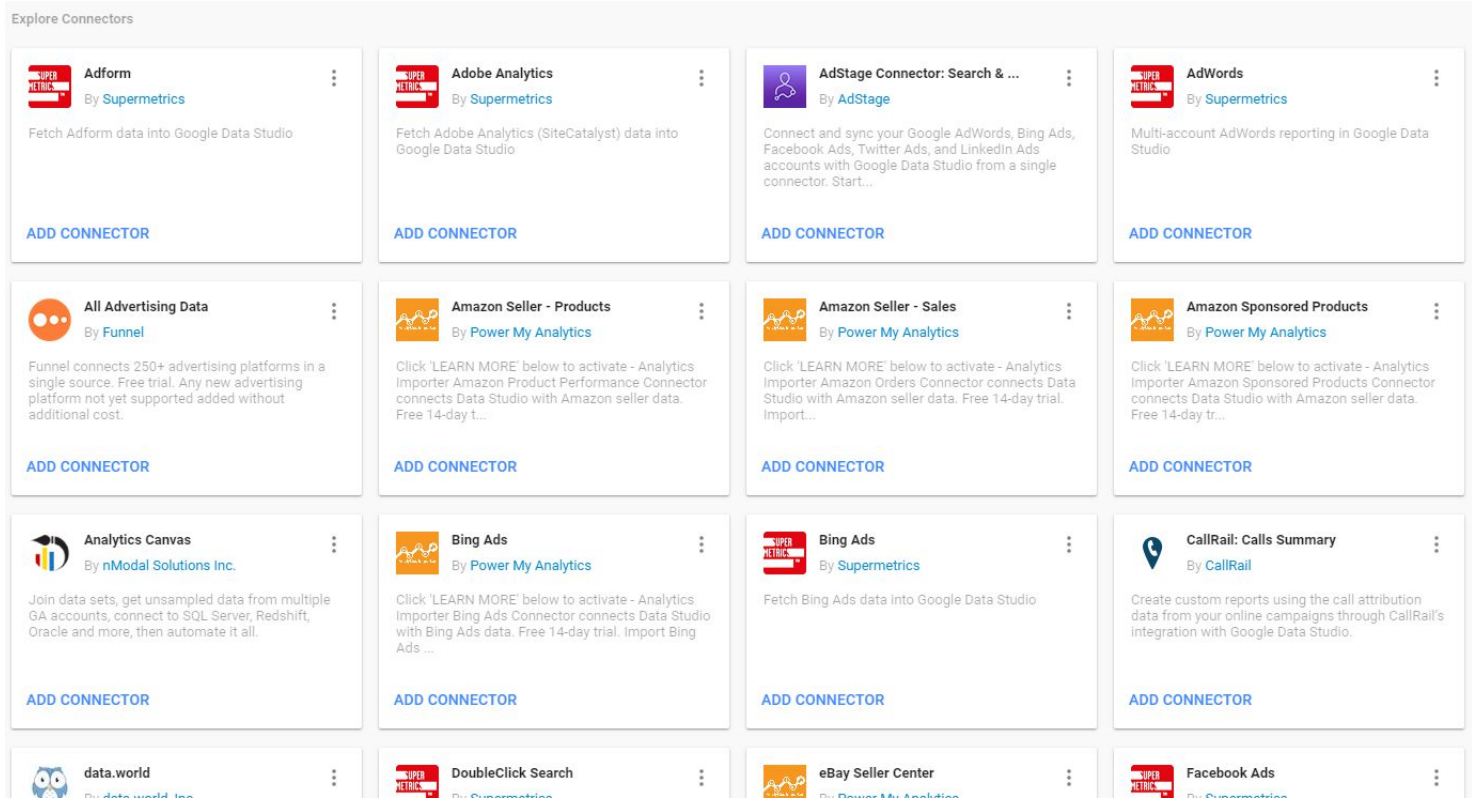
2 basic types of data sets:

Fixed schema	Flexible schema
We understand the data before we ingest it	No idea what the data is before we ingest it
• Google Ads • Search Ads 360 • Google Analytics • Search Console • YouTube Analytics • Display & Video 360	• BigQuery • File upload (CSV) • Google Cloud Storage • Google Sheets • SQL connectors (MySQL, PostgreSQL)

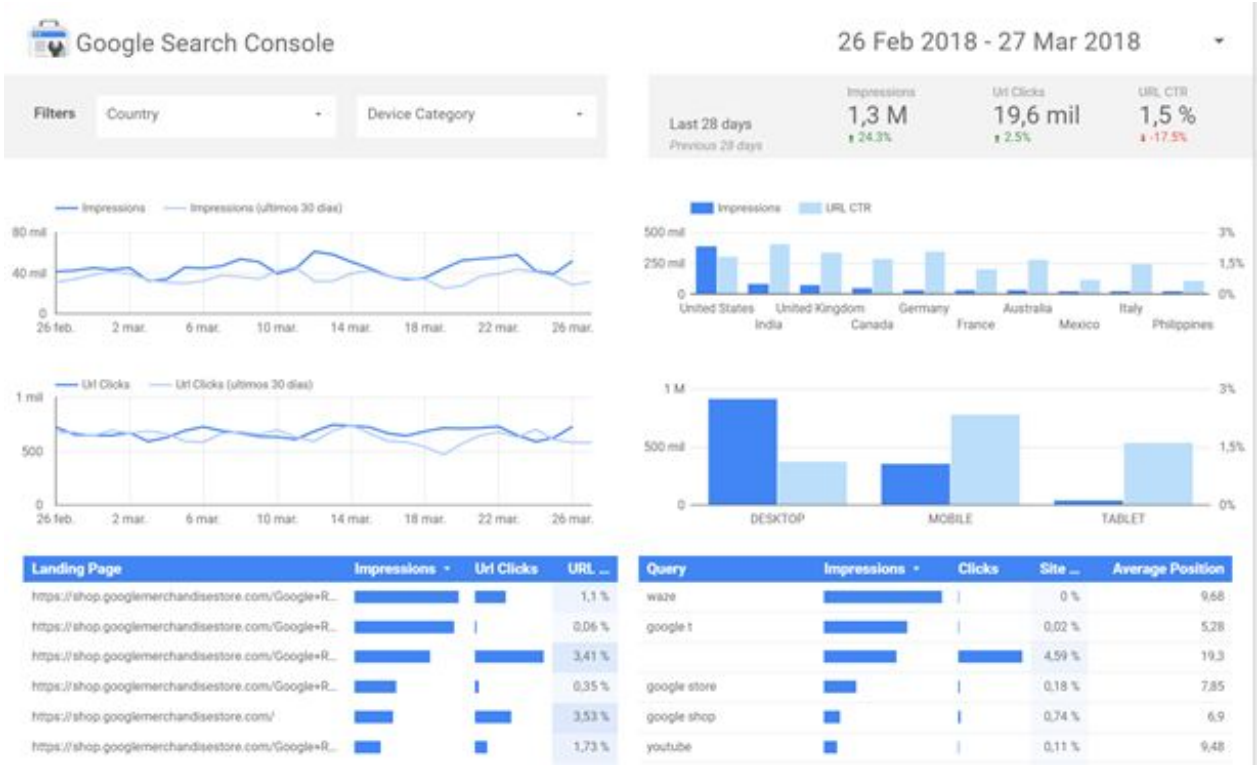
Data Studio connectors



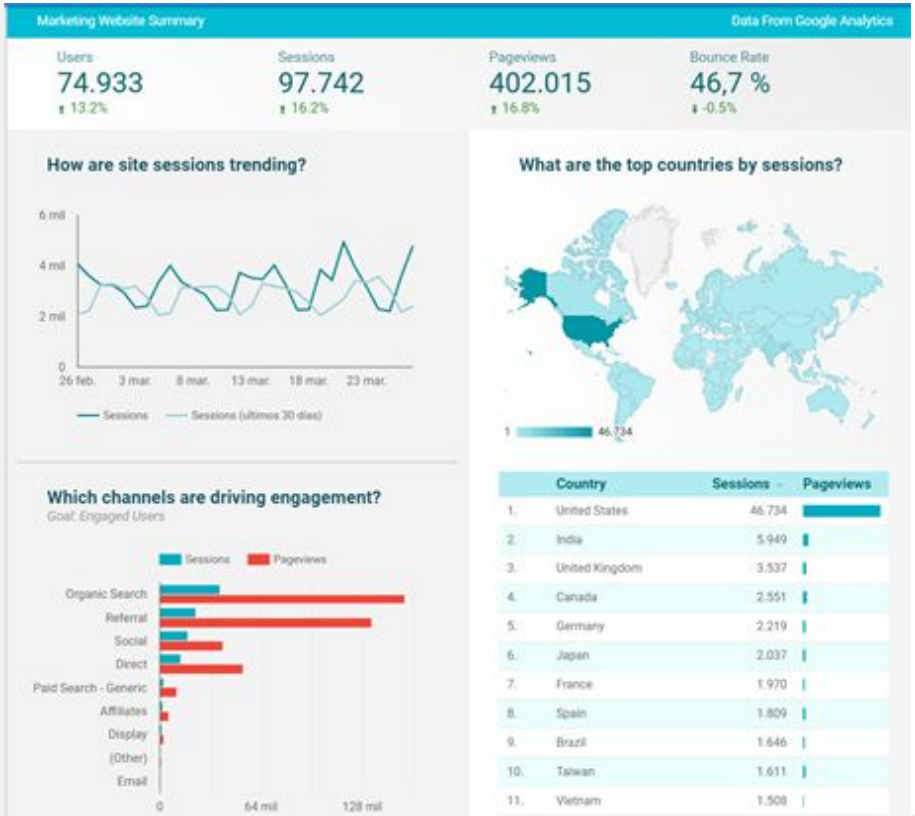
… and more!

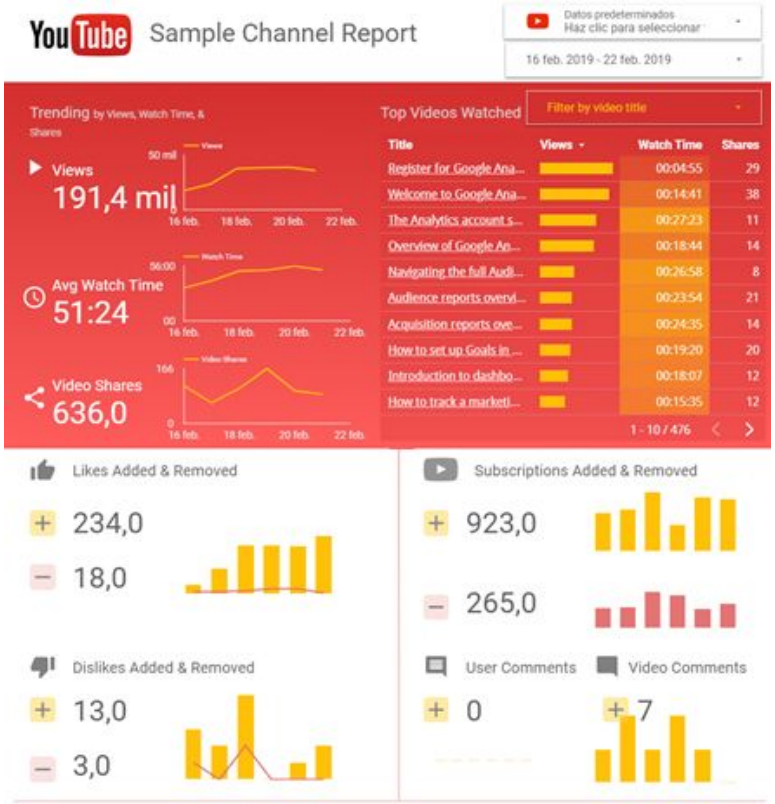

Explore Connectors
Adform
By Supermetrics
Fetch Adform data into Google Data Studio
ADD CONNECTOR
Adobe Analytics
By Supermetrics
Fetch Adobe Analytics (SiteCatalyst) data into Google Data Studio
ADD CONNECTOR
AdStage Connector: Search & ...
By AdStage
Connect and sync your Google AdWords, Bing Ads, Facebook Ads, Twitter Ads, and Linkedin Ads accounts with Google Data Studio from a single connector. Start...
ADD CONNECTOR
AdWords
By Supermetrics
Multi-account AdWords reporting in Google Data Studio
ADD CONNECTOR
All Advertising Data
By Funnel
Funnel connects 250+ advertising platforms in a single source. Free trial. Any new advertising platform not yet supported added without additional cost.
ADD CONNECTOR
Amazon Seller - Products
By Power My Analytics
Click 'LEARN MORE' below to activate - Analytics Importer Amazon Product Performance Connector connects Data Studio with Amazon seller data. Free 14-day t...
ADD CONNECTOR
Amazon Seller - Sales
By Power My Analytics
Click 'LEARN MORE' below to activate - Analytics Importer Amazon Orders Connector connects Data Studio with Amazon seller data. Free 14-day trial. Import...
ADD CONNECTOR
Amazon Sponsored Products
By Power My Analytics
Click 'LEARN MORE' below to activate - Analytics Importer Amazon Sponsored Products Connector connects Data Studio with Amazon seller data. Free 14-day tr...
ADD CONNECTOR
Analytics Canvas
By nModal Solutions Inc.
Join data sets, get unsampled data from multiple GA accounts, connect to SQL Server, Redshift, Oracle and more, then automate it all.
ADD CONNECTOR
Bing Ads
By Power My Analytics
Click 'LEARN MORE' below to activate - Analytics Importer Bing Ads Connector connects Data Studio with Bing Ads data. Free 14-day trial. Import Bing Ads ...
ADD CONNECTOR
Bing Ads
By Supermetrics
Fetch Bing Ads data into Google Data Studio
ADD CONNECTOR
CallRail: Calls Summary
By CallRail
Create custom reports using the call attribution data from your online campaigns through CallRail's integration with Google Data Studio.
ADD CONNECTOR
data.world
DoubleClick Search
eBay Seller Center
Facebook Ads

examples

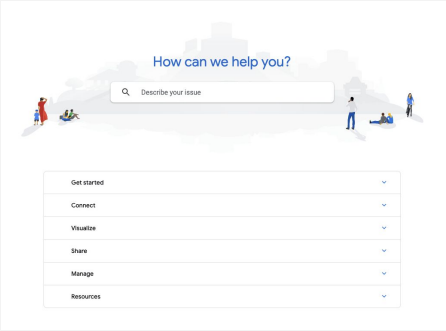

Google Search Console
26 Feb 2018 - 27 Mar 2018
Filters
Country
Device Category
Last 28 days
Previous 28 days
Impressions
1,3 M
24.3%
Url Clicks
19,6 mil
2.5%
URL CTR
1,5 %
-17.5%
Impressions
Impressions (ultimos 30 dias)
80 mil
40 mil
0
26 feb.
2 mar.
6 mar.
10 mar.
14 mar.
18 mar.
22 mar.
26 mar.
Impressions
URL CTR
500 mil
250 mil
0
3%
1,5%
0%
United States
India
United Kingdom
Canada
Germany
France
Australia
Mexico
Italy
Philippines
Url Clicks
Url Clicks (ultimos 30 dias)
1 mil
500
0
26 feb.
2 mar.
6 mar.
10 mar.
14 mar.
18 mar.
22 mar.
26 mar.
1 M
500 mil
0
3%
1,5%
0%
DESKTOP
MOBILE
TABLET
Landing Page
Impressions
Url Clicks
URL ...
https://shop.googlemerchandisestore.com/Google+R... 1,1 %
https://shop.googlemerchandisestore.com/Google+R... 0,06 %
https://shop.googlemerchandisestore.com/Google+R... 3,41 %
https://shop.googlemerchandisestore.com/Google+R... 0,35 %
https://shop.googlemerchandisestore.com/ 3,53 %
https://shop.googlemerchandisestore.com/Google+R... 1,73 %
Query
Impressions
Clicks
Site ...
Average Position
waze 0 % 9,68
google t 0,02 % 5,28
4,59 % 19,3
google store 0,18 % 7,85
google shop 0,74 % 6,9
youtube 0,11 % 9,48

examples

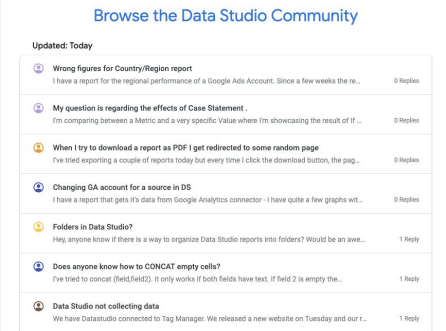

Marketing Website Summary
Data From Google Analytics
Users
74.933
13.2%
Sessions
97.742
16.2%
Pageviews
402.015
16.8%
Bounce Rate
46,7 %
-0.5%
How are site sessions trending?
6 mil
4 mil
2 mil
0
26 feb.
3 mar.
8 mar.
13 mar.
18 mar.
23 mar.
Sessions
Sessions (ultimos 30 días)
What are the top countries by sessions?
1
46.734
Which channels are driving engagement?
Goal: Engaged Users
Sessions
Pageviews
Organic Search
Referral
Social
Direct
Paid Search - Generic
Affiliates
Display
(Other)
Email
0
64 mil
128 mil
Country
Sessions
Pageviews
1. United States 46.734
2. India 5.949
3. United Kingdom 3.537
4. Canada 2.551
5. Germany 2.219
6. Japan 2.037
7. France 1.970
8. Spain 1.809
9. Brazil 1.646
10. Taiwan 1.611
11. Vietnam 1.508


YouTube
Sample Channel Report
Datos predeterminados
Haz clic para seleccionar
16 feb. 2019 - 22 feb. 2019
Trending by Views, Watch Time, & Shares
Views
191,4 mil
Avg Watch Time
51:24
Video Shares
636,0
16 feb.
18 feb.
20 feb.
22 feb.
Top Videos Watched
Filter by video title
Title
Views
Watch Time
Shares
Register for Google Ana... 00:04:55 29
Welcome to Google Ana... 00:14:41 38
The Analytics account s... 00:27:23 11
Overview of Google An... 00:18:44 14
Navigating the full Audi... 00:26:58 8
Audience reports overvi... 00:23:54 21
Acquisition reports ove... 00:24:35 14
How to set up Goals in ... 00:19:20 20
Introduction to dashbo... 00:18:07 12
How to track a marketi... 00:15:35 12
1 - 10 / 476
Likes Added & Removed
+ 234,0
– 18,0
Subscriptions Added & Removed
+ 923,0
– 265,0
Dislikes Added & Removed
+ 13,0
– 3,0
User Comments
+ 0
Video Comments
+ 7

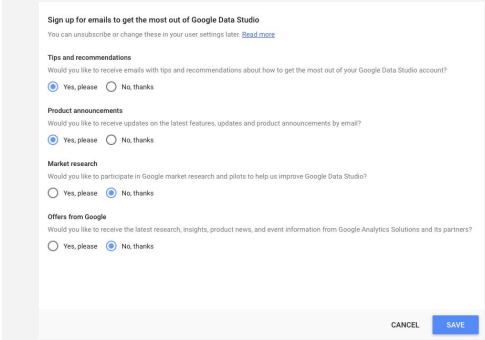
Further Data Studio resources



[Help center]



[Community forums]



Product updates
(opt-in in user settings)

Agenda

01 Introduccion a BigQuery

02 Conceptos básicos de Standard SQL

Break (🎉🎉)

03 DataStudio como herramienta de Visualización

04 Ejercicio práctico BigQuery y DataStudio

05 BigQuery GeoViz

Fin (🎉🎉)

BigQuery + DataStudio Exercise

Upload Raw Data

Manipulate in SQL

Visualize in DataStudio

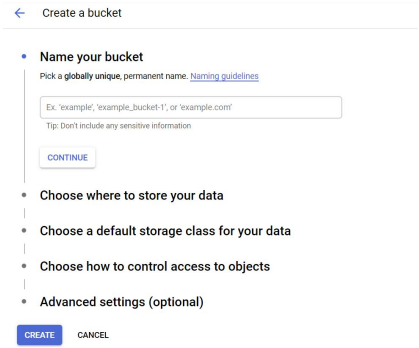
BigQuery + DataStudio Exercise

Upload Raw Data

Import Raw Data from Google Cloud Storage

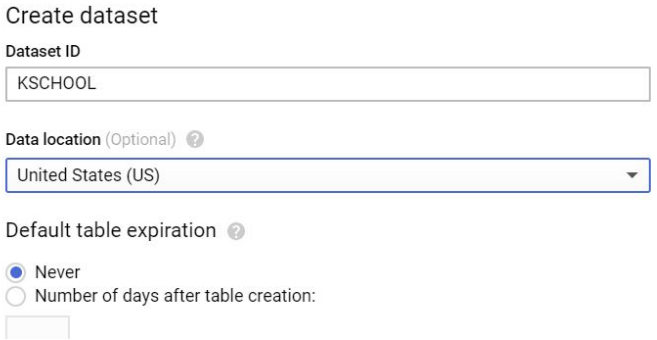
Upload data_clase_2019 and currency_mapping_2019 to Google Cloud Storage

Create a Google Cloud Storage Bucket and upload both files



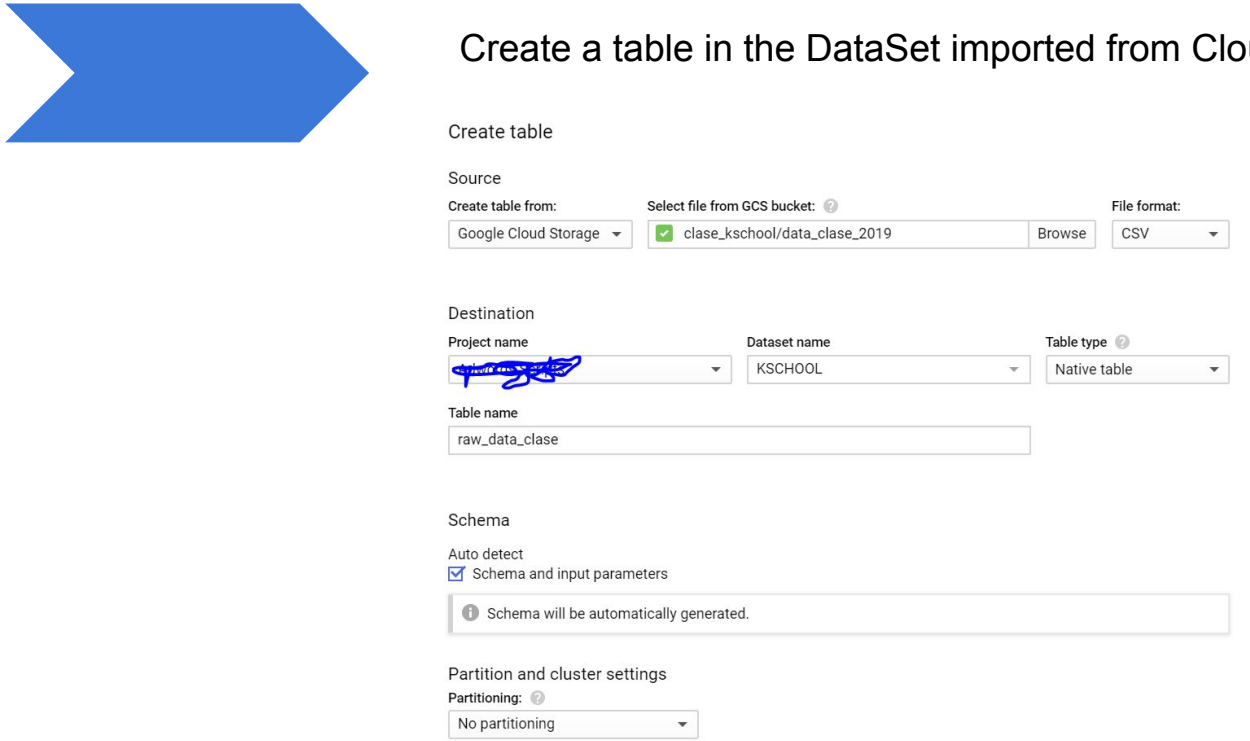
Import Raw Data from Google Cloud Storage

From BigQuery, Create a DataSet with the same region as the Cloud storage bucket



Import Raw Data from Google Cloud Storage

Create a table in the DataSet imported from Cloud Storage



BigQuery + DataStudio Exercise

Manipulate in SQL

BigQuery + DataStudio Exercise

Understand DataSet - Preview

Row	Network	Device	startofmonth	Campaign	CustomerId	Type	clicks	cost	impressions	conversions	ImpressionSum
1	Search Network	Computers	2016-02-01 00:00:00 UTC	CAMP1	C1	Brand	224	1566.3	2078	10	3533.4
2	Search Network	Computers	2016-01-01 00:00:00 UTC	CAMP1	C1	Brand	224	298.06	2422	8	5093.6
3	Search Network	Computers	2015-10-01 00:00:00 UTC	CAMP1	C1	Brand	258	283.8	2596	58	5453.6
4	Search Network	Computers	2016-03-01 00:00:00 UTC	CAMP1	C1	Brand	274	2279.94	2056	34	3437.8
5	Search Network	Computers	2015-08-01 00:00:00 UTC	CAMP1	C1	Brand	220	376.1	2168	84	4713.4
6	Search Network	Computers	2016-04-01 00:00:00 UTC	CAMP1	C1	Brand	126	159.58	1414	8	3206.2
7	Search Network	Computers	2015-05-01 00:00:00 UTC	CAMP1	C1	Brand	312	273.3	3244	40	6705.4
8	Search Network	Computers	2015-09-01 00:00:00 UTC	CAMP1	C1	Brand	224	294.94	2414	32	5188.6

BigQuery + DataStudio Exercise

Understand DataSet - Preview

Network: Search (Google Search Ads) Or Display (Google Display Banner Ads)
Device: Computer, Mobile or tablet where the ad was shown
StartOfMonth: First day of Month timestamp
Campaign: Campaign Associated with the Ad
CustomerId: Billing Customer Id for Google Ads
Type: Type and description of Campaign: Brand / Generic / Audiences
Clicks: number of Clicks driven by the Ads
Cost: Cost Associated to the ads
Impressions: total of impressions shown
Conversion: Goal actions achieved by ads
ImpressionSum = Position of the ad * Impressions

BigQuery + DataStudio Exercise

Create a Table that includes country, exchange rante and metrics to calculare YoY of 2016 Vs 2015

BigQuery + DataStudio Exercise

Solution

```
select
country, month,tipocambio,network,Device,type,campaign,currency, sum(clicks) as clicks, sum(cost)/tipocambio as costeur,sum(impressions) as impressions,
sum(conversions) as conversions,sum(impressionSum) as impressionSum,sum(cost2015)/tipocambio as cost2015,sum(cost2016)/tipocambio as cost2016,
sum(conversions2015) as conversions2015,sum(conversions2016) as conversions2016,sum(impressions2015) as impressions2015,sum(impressions2016) as
impressions2016,
sum(ImpressionSum2015) as ImpressionSum2015,sum(ImpressionSum2016) as ImpressionSum2016
 from (
select
t2.country as country,t2.TC as tipocambio,  t1.startofmonth as month, t1.Network as network, t1.Device as Device,
        t1.Type as type, t1.Campaign as campaign, t2.Currency as currency,
        sum(t1.clicks) as clicks, sum(t1.cost) as cost, sum(t1.impressions) as impressions, sum(t1.conversions) as conversions,
        sum(t1.ImpressionSum) as ImpressionSum,
        sum(if(extract(year from t1.startofmonth )= 2016,t1.cost,0)) as cost2016,
        sum(if(extract(year from t1.startofmonth )= 2015,t1.cost,0)) as cost2015,
        sum(if(extract(year from t1.startofmonth )= 2016,t1.conversions,0)) as conversions2016,
        sum(if(extract(year from t1.startofmonth )= 2015,t1.conversions,0)) as conversions2015,
        sum(if(extract(year from t1.startofmonth )= 2016,t1.impressions,0)) as impressions2016,
        sum(if(extract(year from t1.startofmonth )= 2015,t1.impressions,0)) as impressions2015,
        sum(if(extract(year from t1.startofmonth )= 2016,t1.ImpressionSum,0)) as ImpressionSum2016,
        sum(if(extract(year from t1.startofmonth )= 2015,t1.ImpressionSum,0)) as ImpressionSum2015
           from CLASE2.RAW as t1 INNER JOIN CLASE2.Mapping as t2
           on t1.CustomerId = t2.Accountid
           group by 1,2,3,4,5,6,7,8)
           group by 1,2,3,4,5,6,7,8
```

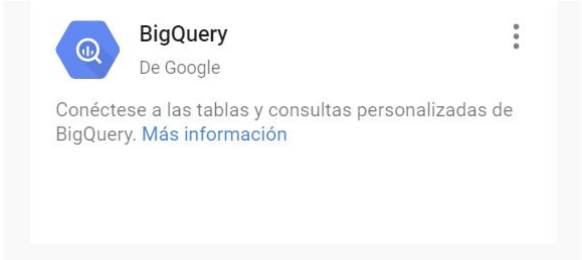
BigQuery + DataStudio Exercise

Visualize in DataStudio

BigQuery + DataStudio Exercise

Create DataSource in DataStudio from saved BigQuery Table

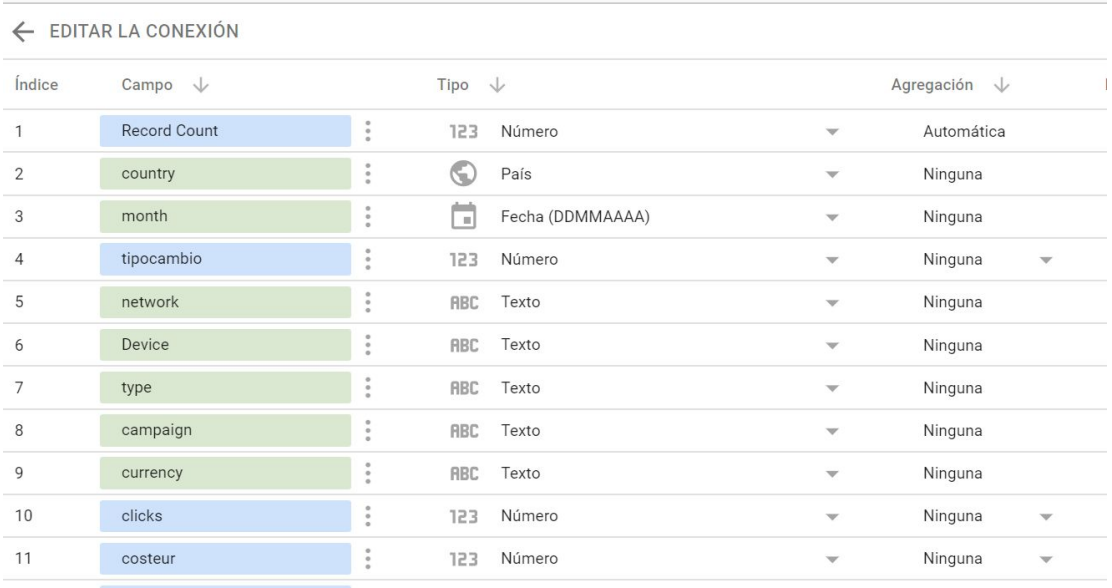
Select BigQuery as source



Select the table and click connect

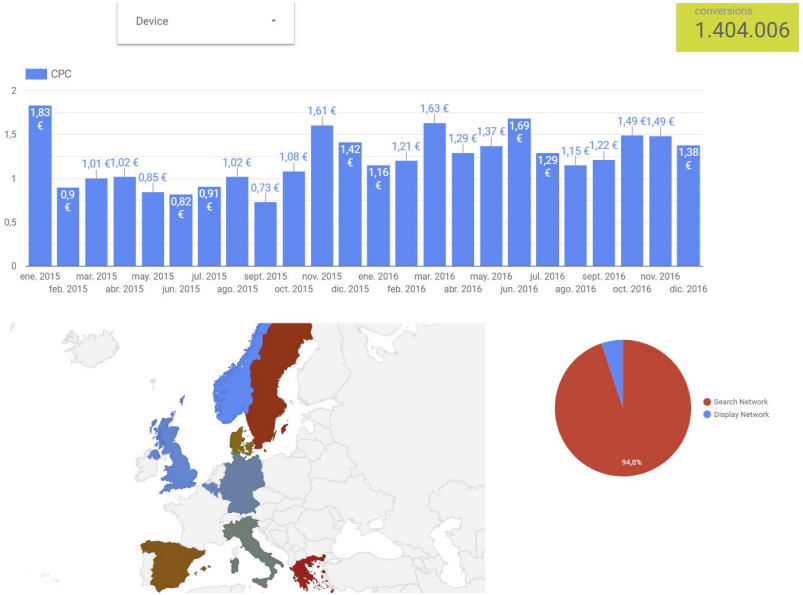
BigQuery + DataStudio Exercise

Adapt Fields and create calculated fields



BigQuery + DataStudio Exercise

Create Report from DataSource



BigQuery + DataStudio Exercise

Share the report to collaborate or to share Visualizations

Action	Public	Can view	Can edit	Is owner
View data in the report (depending on data source credentials)	x	x	x	x
Copy the report		x	x	x
Prevent report copying				x
Share the report with others		x	x	x
Prevent report sharing				x
Modify the report			x	x
Use and modify data from added data sources			x	x
Add / remove data sources			x	x
Create / delete the report				x
Download data from the report	x	x	x	x
Prevent downloading data				x

Agenda

01 Introduccion a BigQuery

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Break (🎉🎉)

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05 BigQuery GeoViz

Fin (🎉🎉)

Analyze GIS data in BigQuery with familiar SQL

Accurate spatial analyses with **Geography** data type

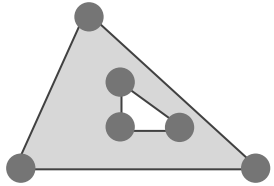
Support for core **GIS functions** – measurements, transforms, constructors, etc... – **using familiar SQL**

Data type:

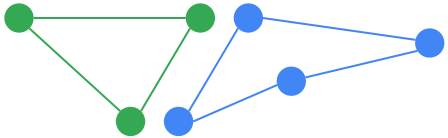
Point

Linestring

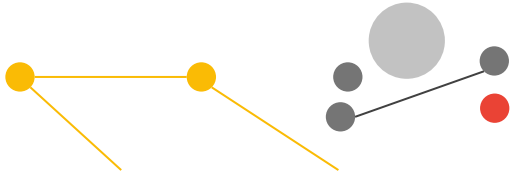
Polygon



Multi-polygon



Collections



Formats:

WKT
GeoJSON
WKB

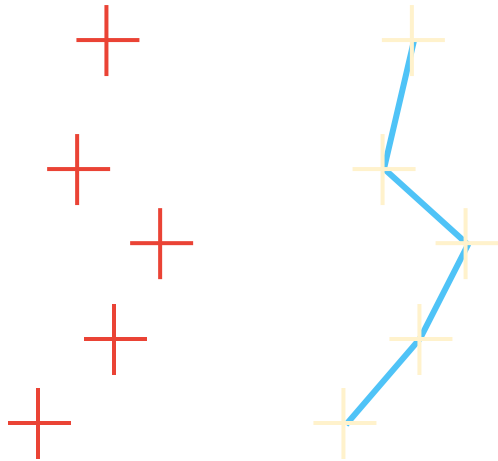
Native SQL support for the most commonly used ST_* functions and geographic data types

Functions	Description
Constructors	Constructive operations build new geography literals from coordinates or existing geographies.
Transformations	Operations that return a single Geography from one or more distinct geographies (e.g., ST_Union)
Predicates	Predicate operations return true/false for some spatial relationship between two geometries. Most frequently used in filter clauses.
Accessors	Operations that let users navigate and select between multiple ways of handling a record based on its type, or select a particular element.
Measures	Measure operations compute some property of the geography such as perimeter, area, or distance to another geography.
Parsers	Operations that construct a Geography from raw coordinates or other geographies.
Formatters	Formatting operations return a geography converted into a standardized (usually string) format suitable for presenting in query results.

Constructors

ST_GEOGPOINT(longitude, latitude)
ST_MAKELINE(geography_1, geography_2)
ST_MAKELINE(array_of_geography)
ST_MAKEPOLYGON(geography_expression)
ST_MAKEPOLYGON(geography_expression, array_of_geography)
ST_MAKEPOLYGONORIENTED(array_of_geography)

Build geographies from
coordinates or existing geographies

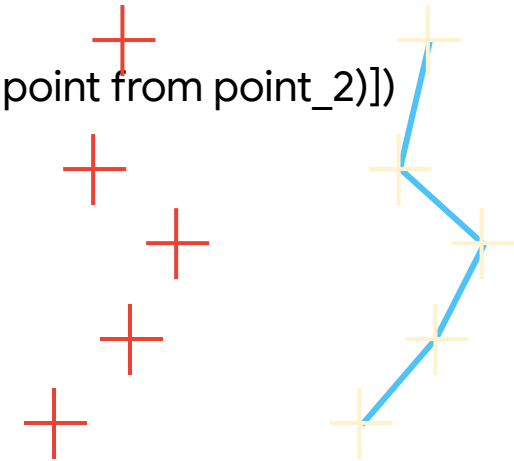


Constructors

```
with
point_1 as (select ST_GEOGPOINT(longitude, latitude) as point,case_number from
`bigquery-public-data.chicago_crime.crime` limit 1),
    point_2 as ((select ST_GEOGPOINT(longitude,latitude) as point from
`bigquery-public-data.chicago_crime.crime` where case_number not in (select
case_number from point_1) limit 1))

    select ST_MAKELINE([(select point from point_1),(select point from point_2)])
```

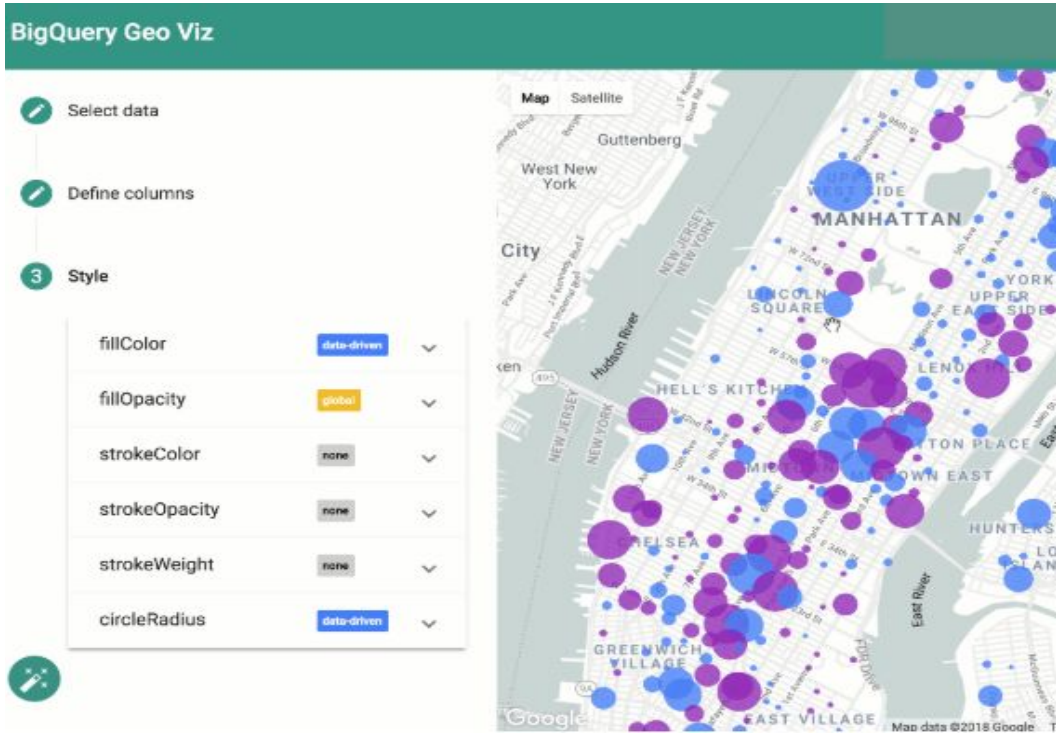
Build geographies from
coordinates or existing geographies



Google Cloud

GEO VIZ UI

Test in GeoViz UI

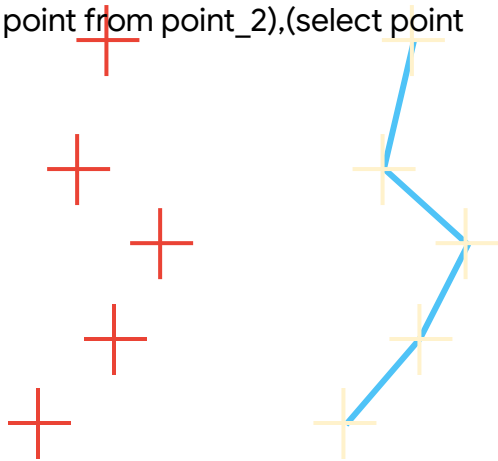



Google Cloud

Constructors

```
with point_1 as (select ST_GEOGPOINT(longitude, latitude) as point,case_number from
`bigquery-public-data.chicago_crime.crime` limit 1),
    point_2 as ((select ST_GEOGPOINT(longitude, latitude) as point,case_number from
`bigquery-public-data.chicago_crime.crime` where case_number not in (select case_number from point_1) limit
1)),
     point_3 as ((select ST_GEOGPOINT(longitude, latitude) as point from
`bigquery-public-data.chicago_crime.crime` where case_number not in (select case_number from point_1)
     and case_number not in (select case_number from point_2) limit 1))
    select ST_MAKEPOLYGON(ST_MAKELINE([(select point from point_1),(select point from point_2),(select point
from point_3)])) as polygon
```

Build geographies from
coordinates or existing geographies



Google Cloud

Parsers & formatters

```
ST_GEOGFROMGEOJSON(geojson_string)
ST_GEOGFROMTEXT(wkt_string)
ST_GEOGFROMWKB(wkb_bytes)
```

```
ST_ASGEOJSON(geography_expression)
ST_ASTEXT(geography_expression)
ST_ASBINARY(geography_expression)
```

Create/export geographies
between formats

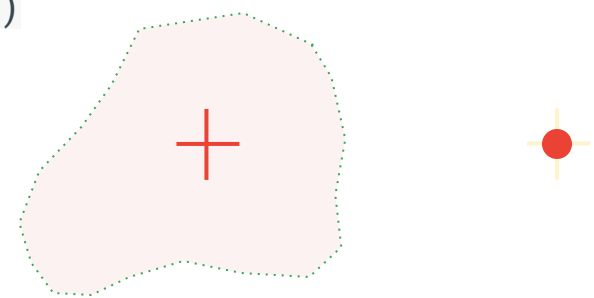
```
((0 0 0, 0 1 0, 1 1 0, 1 0 0, 0 0 0)),
((0 0 0, 0 1 0, 0 1 1, 0 0 1, 0 0 0)),
((0 0 0, 1 0 0, 1 0 1, 0 0 1, 0 0 0)),
((1 1 1, 1 0 1, 0 0 1, 0 1 1, 1 1 1)),
((1 1 1, 1 0 1, 1 0 0, 1 1 0, 1 1 1))
```

Google Cloud

Transformations

```
ST_INTERSECTION(geography_1, geography_2)
ST_UNION(geography_1, geography_2)
ST_UNION(array_of_geography)
ST_UNION_AGG(geography)
ST_DIFFERENCE(geography_1, geography_2)
ST_CENTROID(geography_expression)
ST_CLOSESTPOINT(geography_1, geography_2[,spheroid=FALSE])
ST_BOUNDARY(geography_expression)
ST_SNAPTOGRID(geography_expression, grid_size)
```

Create new geographies
with similar properties

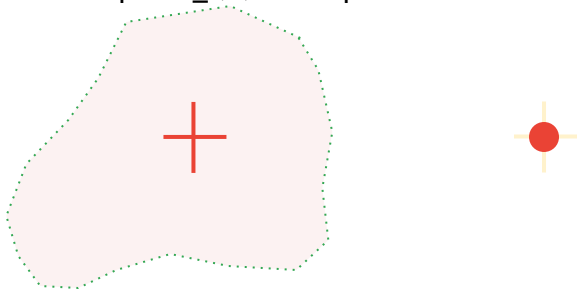


Google Cloud

Transformations

```
with point_1 as (select ST_GEOGPOINT(longitude, latitude) as point,case_number from
`bigquery-public-data.chicago_crime.crime` limit 1),
    point_2 as ((select ST_GEOGPOINT(longitude, latitude) as point,case_number from
`bigquery-public-data.chicago_crime.crime` where case_number not in (select case_number from
point_1) limit 1)),
     point_3 as ((select ST_GEOGPOINT(longitude, latitude) as point from
`bigquery-public-data.chicago_crime.crime` where case_number not in (select case_number from
point_1)
     and case_number not in (select case_number from point_2) limit 1))
   --  select point from point_3
    select ST_CENTROID(ST_MAKEPOLYGON(ST_MAKELINE([(select point from point_1),(select point from
point_2),(select point from point_3)]))) as centroid
```

Create new geographies
with similar properties

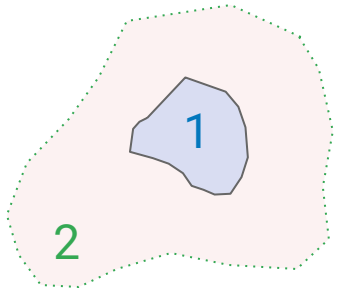


Google Cloud

Predicates

```
ST_CONTAINS(geography_1, geography_2)
ST_COVEREDBY(geography_1, geography_2)
ST_COVERS(geography_1, geography_2)
ST_DISJOINT(geography_1, geography_2)
ST_DWITHIN(geography_1, geography_2, distance[, spheroid=FALSE])
ST_EQUALS(geography_1, geography_2)
ST_INTERSECTS(geography_1, geography_2)
ST_INTERSECTSBOX(geography, lng1, lat1, lng2, lat2)
ST_TOUCHES(geography_1, geography_2)
ST_WITHIN(geography_1, geography_2)
```

Filter geographies
(TRUE/FALSE)



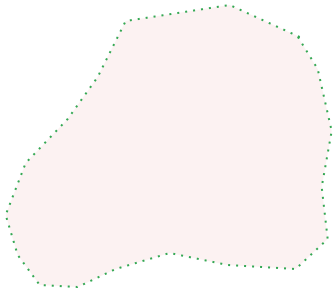
TRUE

Google Cloud

Measures

```
ST_DISTANCE(geography_1, geography_2[, spheroid=FALSE])
ST_LENGTH(geography_expression[, spheroid=FALSE])
ST_PERIMETER(geography_expression[, spheroid=FALSE])
ST_AREA(geography_expression[, spheroid=FALSE])
ST_MAXDISTANCE(geography_1, geography_2[, spheroid=FALSE])
```

Compute measurements
of geographies



3967
(meters)

Google Cloud

GEO VIZ UI

Insert Script in BigQuery Geo Viz

```
SELECT
  ST_GeogPoint(longitude, latitude)  AS WKT,
  num_bikes_available
FROM
  `bigquery-public-data.new_york.citibike_stations`
WHERE num_bikes_available > 30
```

Select Style Fill Color

fillColor data-driven

Fill color of a polygon or point. For example, "linear" or "interval" functions may be used to map numeric values to a color gradient.

Data-driven

Function

linear

Field

num_bikes_available

Domain

31 40 56

min: 31 max: 56

Range

Select Style Radious Circle

circleRadius **data-driven**

Radius of the circle representing a point, in meters. For example, a "linear" function could be used to map numeric values to point sizes, creating a scatterplot style.

Data-driven

Function

linear

Field

num_bikes_available

Domain

31 | 40 | 56

min: 31 | max: 56

Range

Muchas Gracias

Agenda

01	Introducción ML para analistas
02	BigQuery Machine Learning
03	CRM int App engine Application
04	Caso Práctico Iberia
	Break (🎉🎉)
05	Modelo Propensión a Compra según navegación Web
	Fin (🎉🎉)

Agenda

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Fin (🎉🎉)

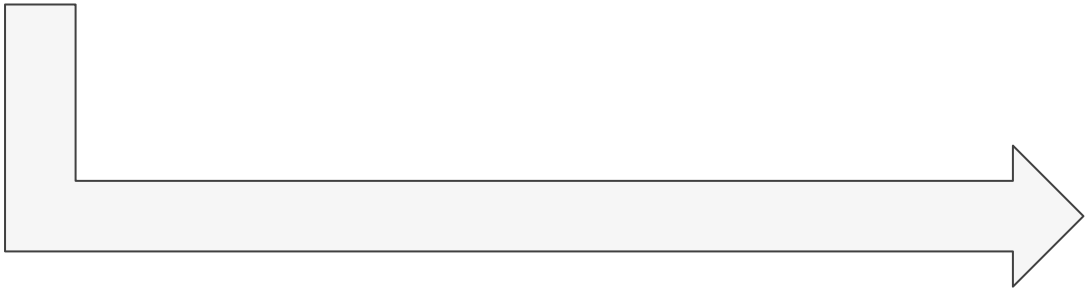
ML For Analysts | What is Machine Learning

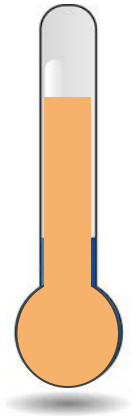
Huge amount of labeled data

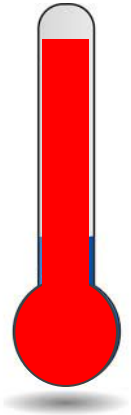
Learn from data (algorithm)

Predict new cases

ML For Analysts | How does Machine Learning work?



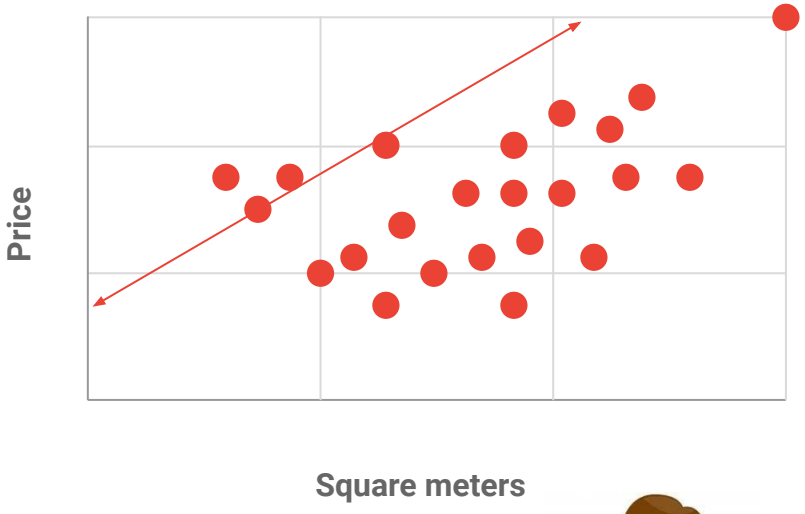




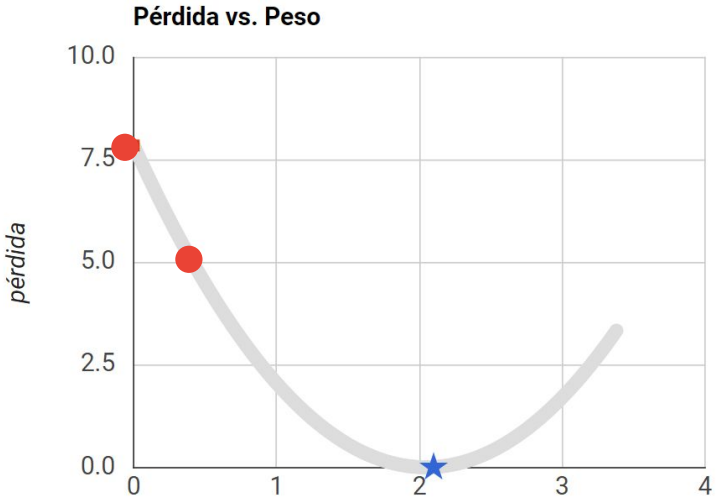
FOUND

Machine learning - How does it work ?

Proposed algorithm

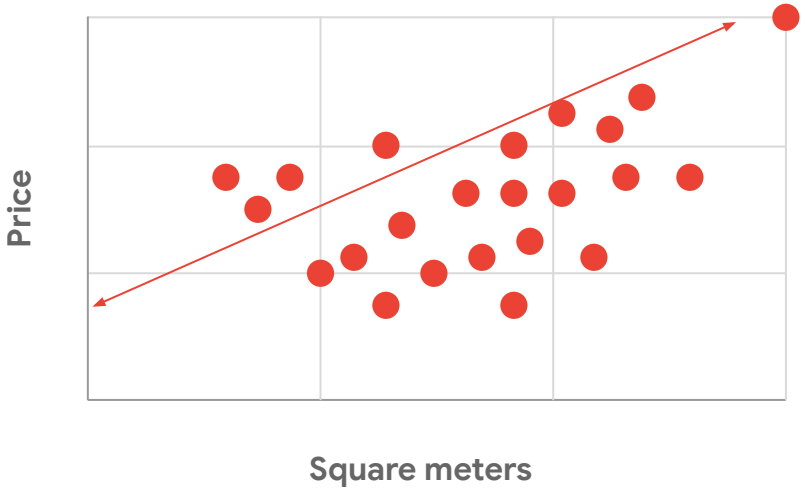


Loss function

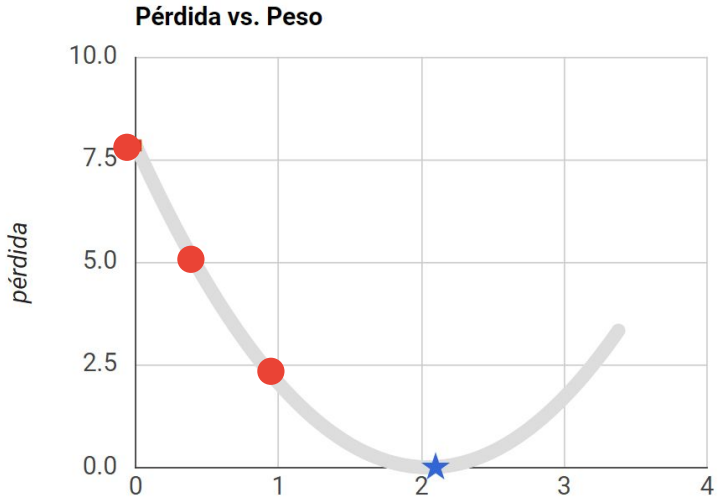


Machine learning - How does it work ?

Proposed algorithm

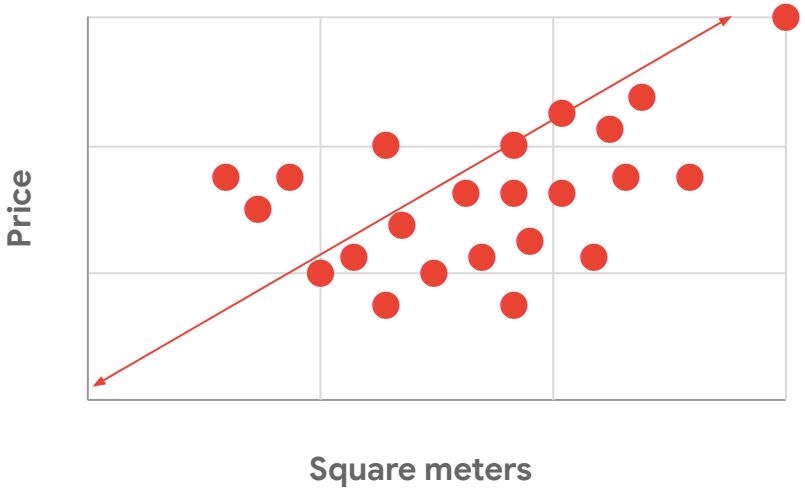


Loss function

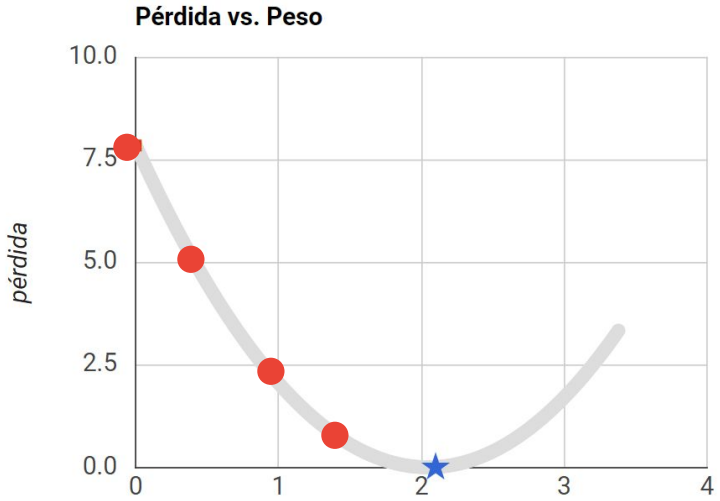


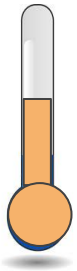
Machine learning - How does it work ?

Proposed algorithm



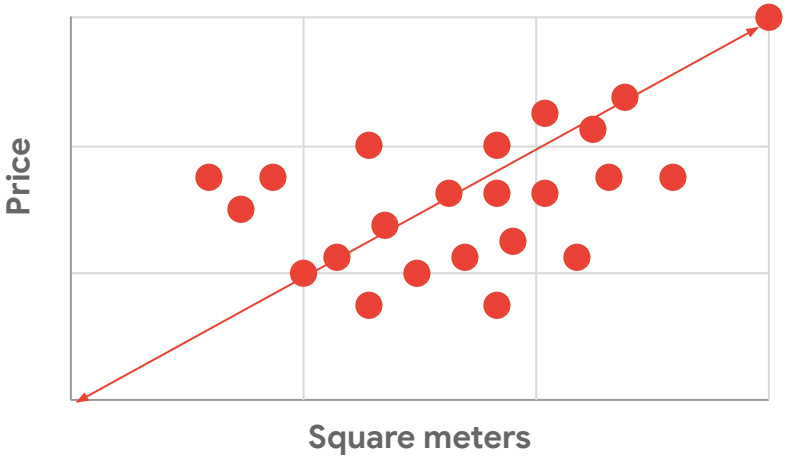
Loss function



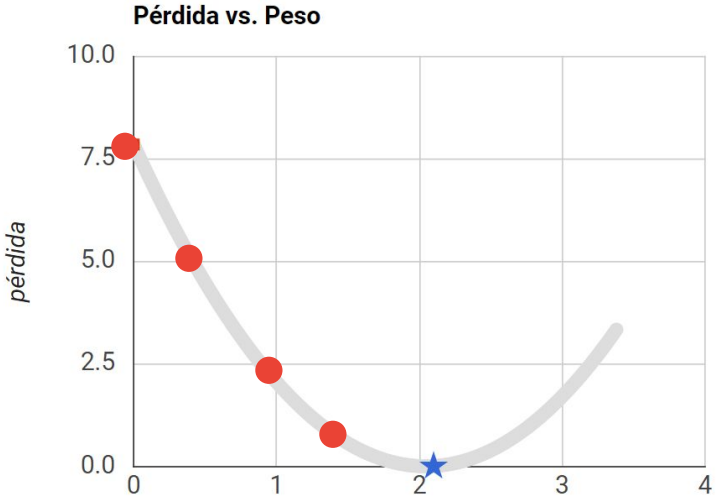


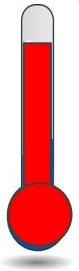
Machine learning - How does it work ?

Proposed algorithm



Loss function





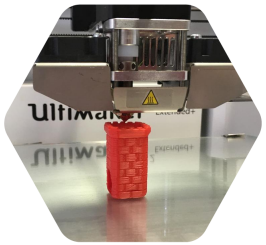
ML For Analysts | What is the process of ML?

Define objectives

Collect data

Understand and prepare the data

Create the model



Refine the model

Serve the model

“

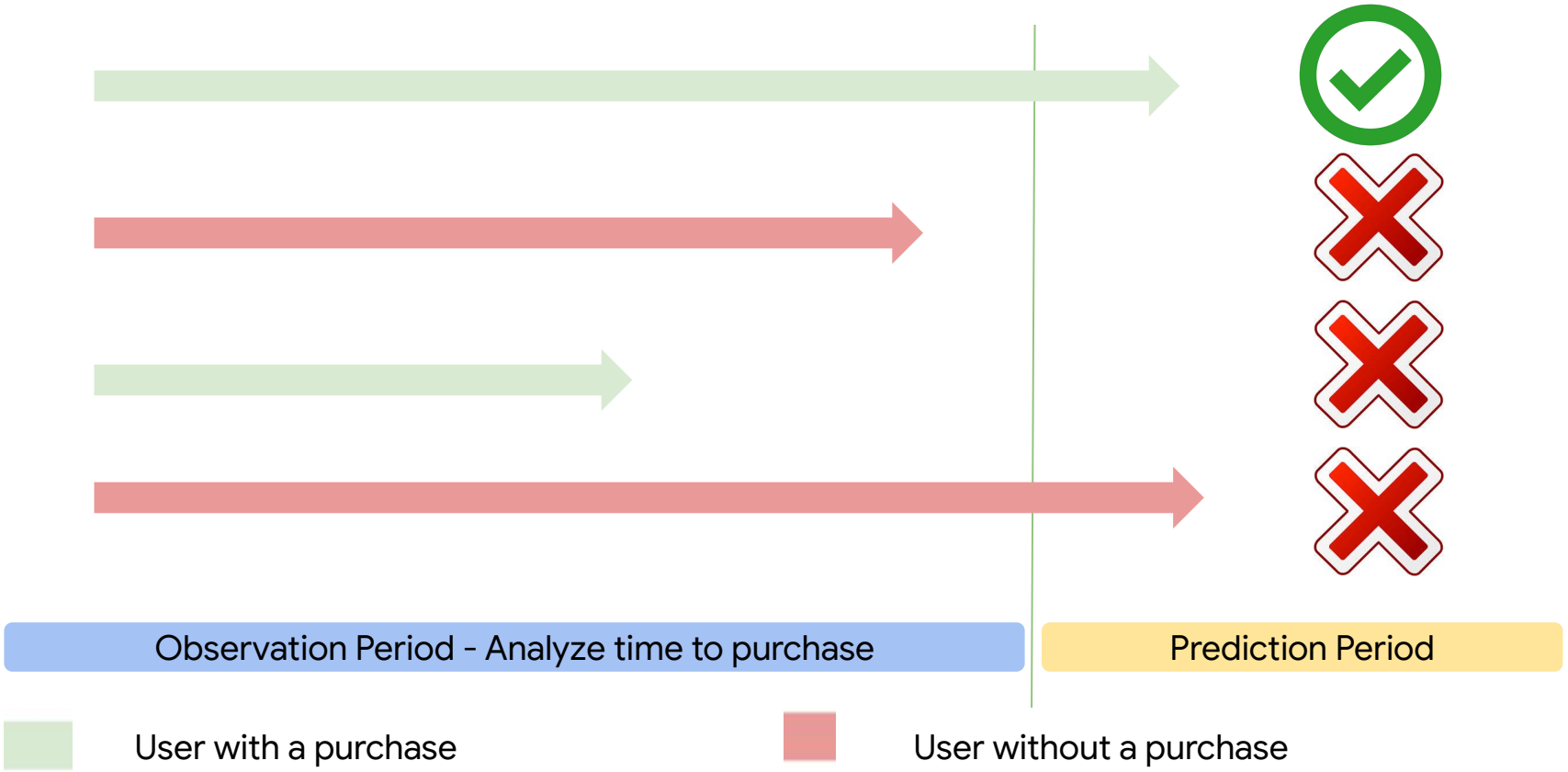
If your company isn’t good at analytics, it’s not ready for AI

– Harvard Business Review , 2017

Collect data

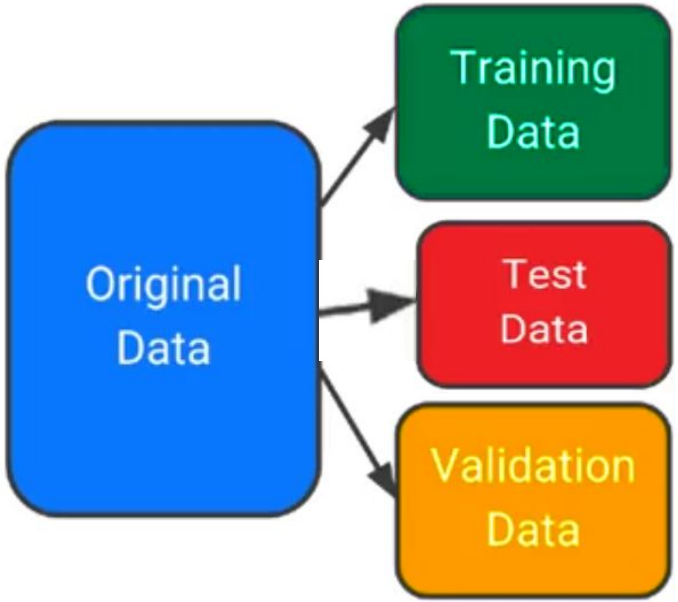
Understand and prepare the data

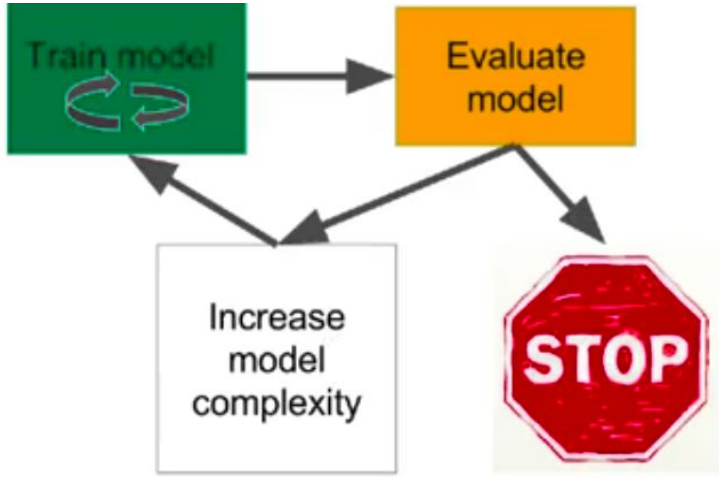
ML For Analysts | Model Design

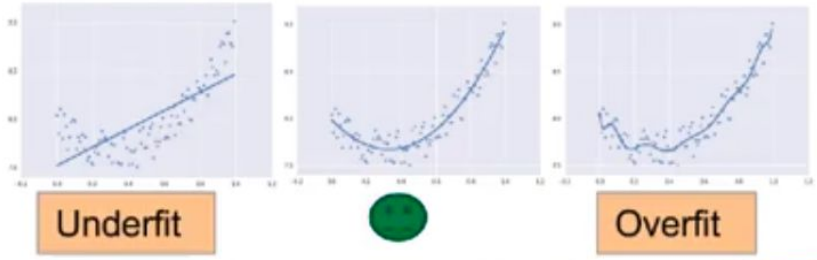


ML For Analysts | Model Evaluation framework

s







ML For Analysts | How to evaluate a model

Classify the cats!

ML For Analysts | How to evaluate a model

		ML System Says	
		Cat	No Cat
Truth	Cat	True Positive #TP	False Negative #FN
	No Cat	False Positive #FP	True Negative #TN

ML For Analysts | How to evaluate a model

Predicted Categories by Model

ML For Analysts | How to evaluate a model

Accuracy: percentage of correct predictions

ML For Analysts | How to evaluate a model

Precision: percentage of correct predictions in positive labels

Accuracy when
ML says “cat”

TP + FP = 5

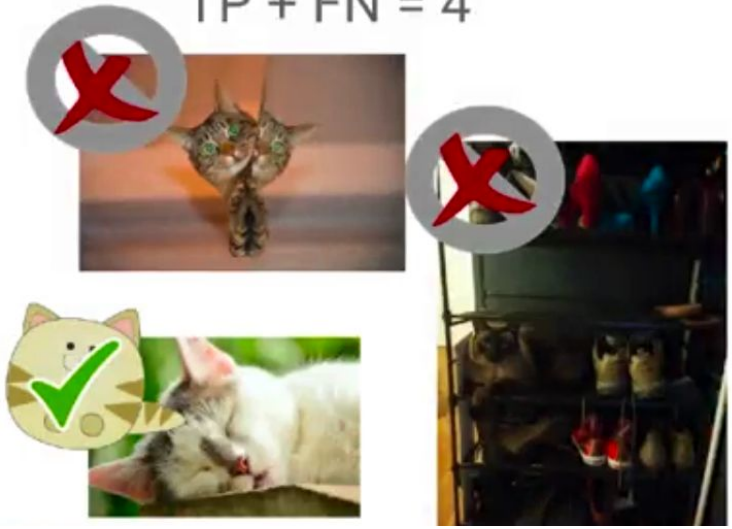
Precision = TP / (TP + FP)
= 2 / 5 = 0.40

ML For Analysts | How to evaluate a model

Recall: percentage of existing positive labels predicted by the model

Recall = fraction of cats ML finds

TP + FN = 4



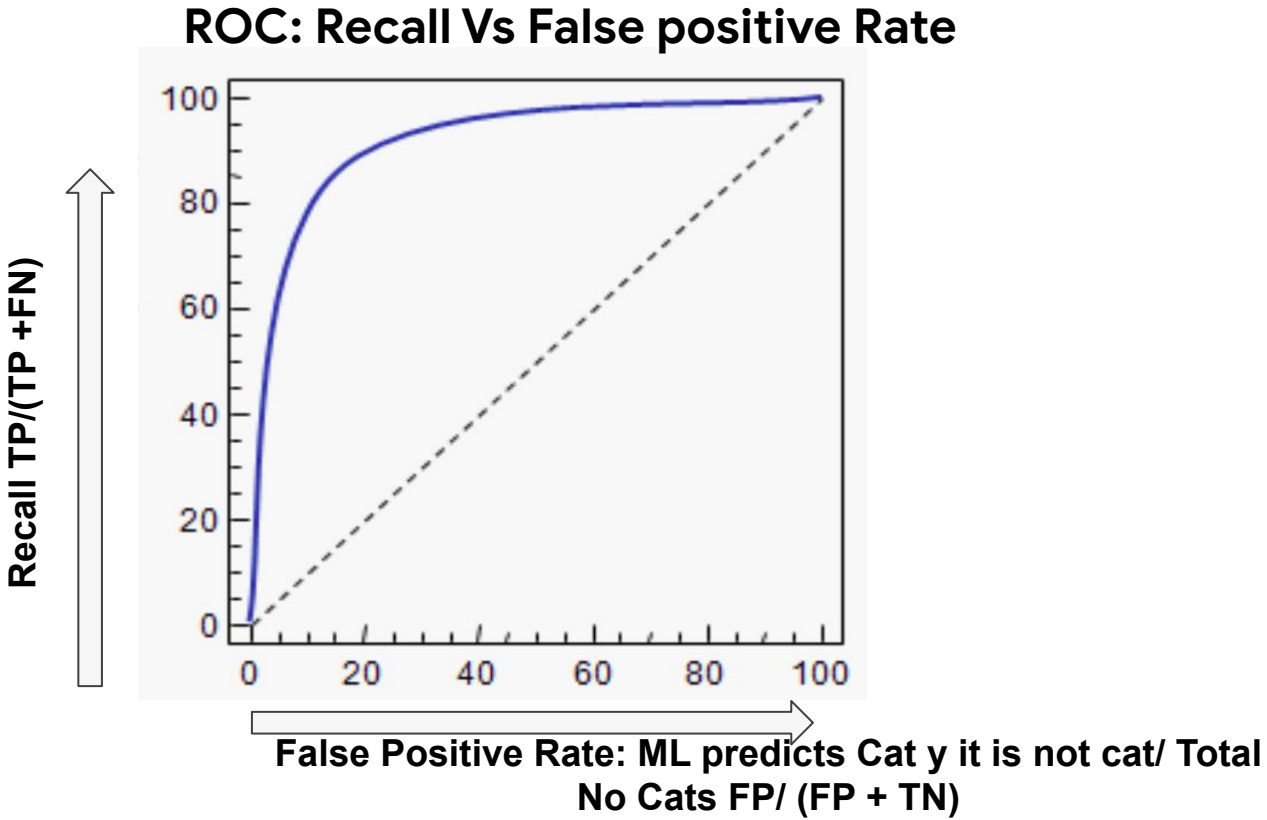
Recall = TP / (TP + FN)

= 2 / 4 = 0.50

ML For Analysts | How to evaluate a model

ML For Analysts | How to evaluate a model

ML For Analysts | How to evaluate a model



Agenda

01 Introducción ML para analistas

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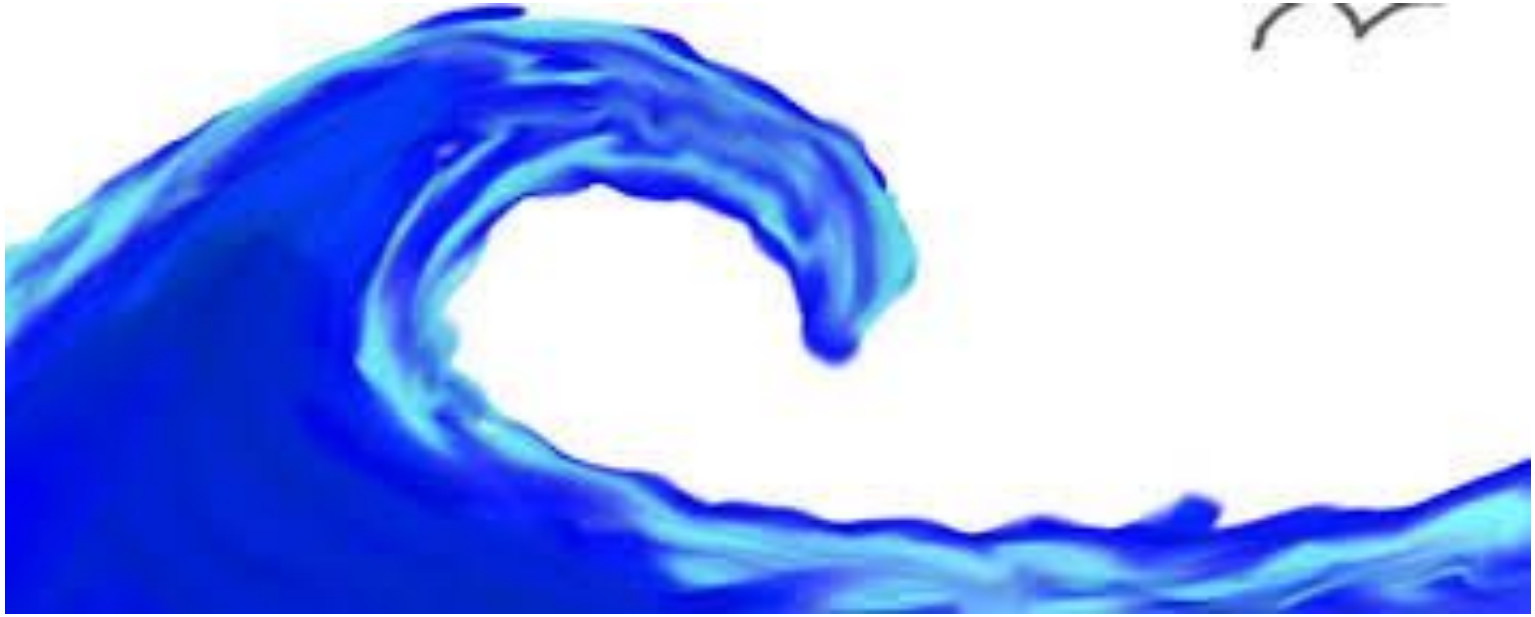
04 Caso Práctico Iberia

Break (🎉🎉)

05 Modelo Propensión a Compra según navegación Web

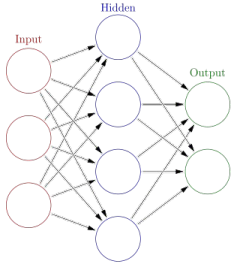
Fin (🎉🎉)

Digital revolutions that changed the world



What these revolutions have in common

ARPANET
THE FIRST INTERNET



1936 1969 1996 1980

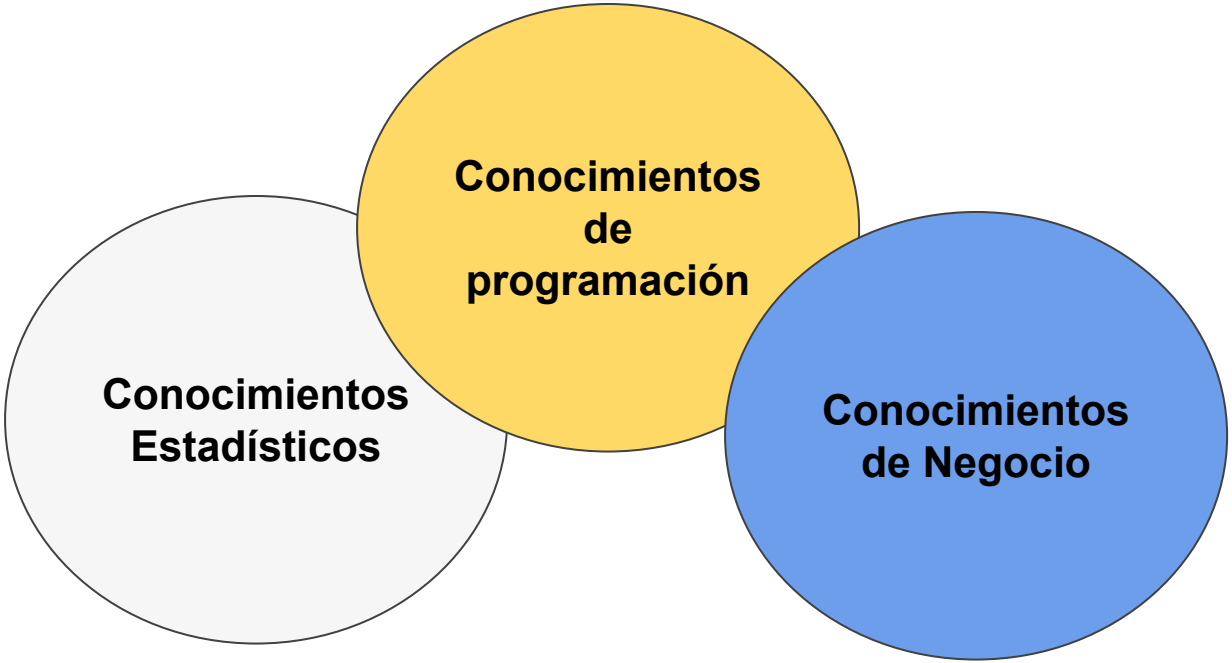
1964 1994 2007 2017

30 Years 13 Years 10 Years

“Today we’re evolving from a mobile first world to an A.I. first world”

- Sundar Pichai, CEO of Google

Being Data Scientist is very complex - Cloud make it easier



Google Cloud is democratizating ML for all audiences

	Novato	Medio	Avanzado	Skills necesarias
TensorFlow y CloudML Engine				• Requires programming and ML knowldge • Google Cloud ML makes production easier and scalable
BQML				• Requires basic ML knowledge • Train, evaluate and predict with SQL language
ML APIs/AutoML				• Basic programming knowledge required • Pre-trained models • Easy to deploy and no ML knowledge required

Machine Learning with SQL

1. **Execute** ML initiatives without moving data from BigQuery
2. **Iterate** on models in SQL in BigQuery to increase development speed
3. **Automate** common ML tasks and hyperparameter tuning

Available Models

- Linear Regression
- Logistic Regression (binary and multiclass)
- Kmeans
- Imported TF model

BQML | Create Model Syntax (link)

```
{CREATE MODEL | CREATE MODEL IF NOT EXISTS | CREATE OR REPLACE MODEL}
model_name
[OPTIONS(model_option_list)]
[AS query_statement]

model_option_list:
 MODEL_TYPE = { 'LINEAR_REG' | 'LOGISTIC_REG' | 'KMEANS' | 'TENSORFLOW' }
 [, INPUT_LABEL_COLS = string_array ]
 [, OPTIMIZE_STRATEGY = { 'AUTO_STRATEGY' | 'BATCH_GRADIENT_DESCENT' | 'NORMAL_EQUATION' } ] →
 [, L1_REG = float64_value ]
 [, L2_REG = float64_value ]
 [, MAX_ITERATIONS = int64_value ]
 [, LEARN_RATE_STRATEGY = { 'LINE_SEARCH' | 'CONSTANT' } ]
 [, LEARN_RATE = float64_value ]
 [, EARLY_STOP = { TRUE | FALSE } ]
 [, MIN_REL_PROGRESS = float64_value ]
 [, DATA_SPLIT_METHOD = { 'AUTO_SPLIT' | 'RANDOM' | 'CUSTOM' | 'SEQ' | 'NO_SPLIT' } ]
 [, DATA_SPLIT_EVAL_FRACTION = float64_value ]
 [, DATA_SPLIT_COL = string_value ]
 [, LS_INIT_LEARN_RATE = float64_value ]
 [, WARM_START = { TRUE | FALSE } ]
 [, AUTO_CLASS_WEIGHTS = { TRUE | FALSE } ]
 [, CLASS_WEIGHTS = struct_array ]
 [, NUM_CLUSTERS = int64_value ]
 [, DISTANCE_TYPE = { 'EUCLIDEAN' | 'COSINE' } ]
 [, STANDARDIZE_FEATURES = { TRUE | FALSE } ]

  [, MODEL_PATH = string_value ]
```

BQML | Evaluate Model Syntax (link)

```
ML.EVALUATE(MODEL model_name
            [, {TABLE table_name | (query_statement)}]

             [, STRUCT(<T> AS threshold)])
```

EXAMPLE

```
SELECT * FROM ML.EVALUATE(MODEL `mydataset.mymodel`, (

  SELECT custom_label, column1, column2

FROM

  `mydataset.mytable`),

STRUCT(0.55 AS threshold))
```

BQML | Evaluate Model Syntax ROC (link)

```
ML.ROC_CURVE(MODEL model_name
             [, {TABLE table_name | (query_statement)}]
             [, GENERATE_ARRAY(thresholds)])
```

EXAMPLE

```
SELECT  * FROM ML.ROC_CURVE(MODEL `mydataset.mymodel`,
    TABLE `mydataset.mytable`)
```

BQML | Evaluate Model Syntax Conf Matrix (link)

```
ML.CONFUSION_MATRIX(MODEL model_name
            [, {TABLE table_name | (query_statement)}]
            [, STRUCT(<T> AS threshold)])
```

EXAMPLE

```
SELECT * FROM  ML.CONFUSION_MATRIX(MODEL `mydataset.mymodel`,  (
    SELECT * FROM
      `mydataset.mytable`))
```

BQML | Predict Model Syntax (link)

```
ML.PREDICT(MODEL model_name,
          {TABLE table_name | (query_statement)}
          [, STRUCT<threshold FLOAT64> settings)])
```

EXAMPLE

```
SELECT  * FROM ML.PREDICT(MODEL `mydataset.mymodel`    (
    SELECT      label,column1,column2
    FROM
      `mydataset.mytable`))
```

BQML | Model Feature Info (link)

Feature information:
```
SELECT * FROM  ML.FEATURE_INFO(MODEL `mydataset.mymodel`)
```

Feature Weights:
```
SELECT category,weight FROM UNNEST((SELECT category_weights FROM
ML.WEIGHTS(MODEL `mydataset.mymodel`) WHERE processed_input = 'input_col'))
```

Kmeans Centroids:
```
SELECT  * FROM ML.CENTROIDS(MODEL `project_id.dataset.model`)
```

Agenda

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Break (🎉🎉)

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Fin (🎉🎉)

CRMint

- A client-side web application for scheduling data flow process between GA 360 and Google ad products for solving business tasks: GA remarketing, LTV, etc.

- Data Pipeline workers
  - Data Import
  - Measurement Protocol
  - GA API data pull to BigQuery
  - Cloud Storage to BigQuery
  - BigQuery to Cloud Storage
  - BigQuery Query launcher
  - Cloud ML model predictor
  - GA audience launcher

‘Deploy CRM int‘

Link

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03 CRM int App engine Application

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Fin (🎉🎉)

‘Iberia ML to predict users probability to convert with BQML‘ - (link)

Iberia uses the power of Machine Learning to identify high value customers

‘Iberia ML to predict users probability to convert with BQML‘ - (link)

1. Improve the average ROAS, by identifying and prioritizing high value customers

2. Tailor the message for high value customers

3. Find users similar to high value customers, using the power of Google Audiences

‘Iberia ML to predict users probability to convert with BQML‘ - (link)

1. Improve the average ROAS, by identifying and prioritizing high value customers

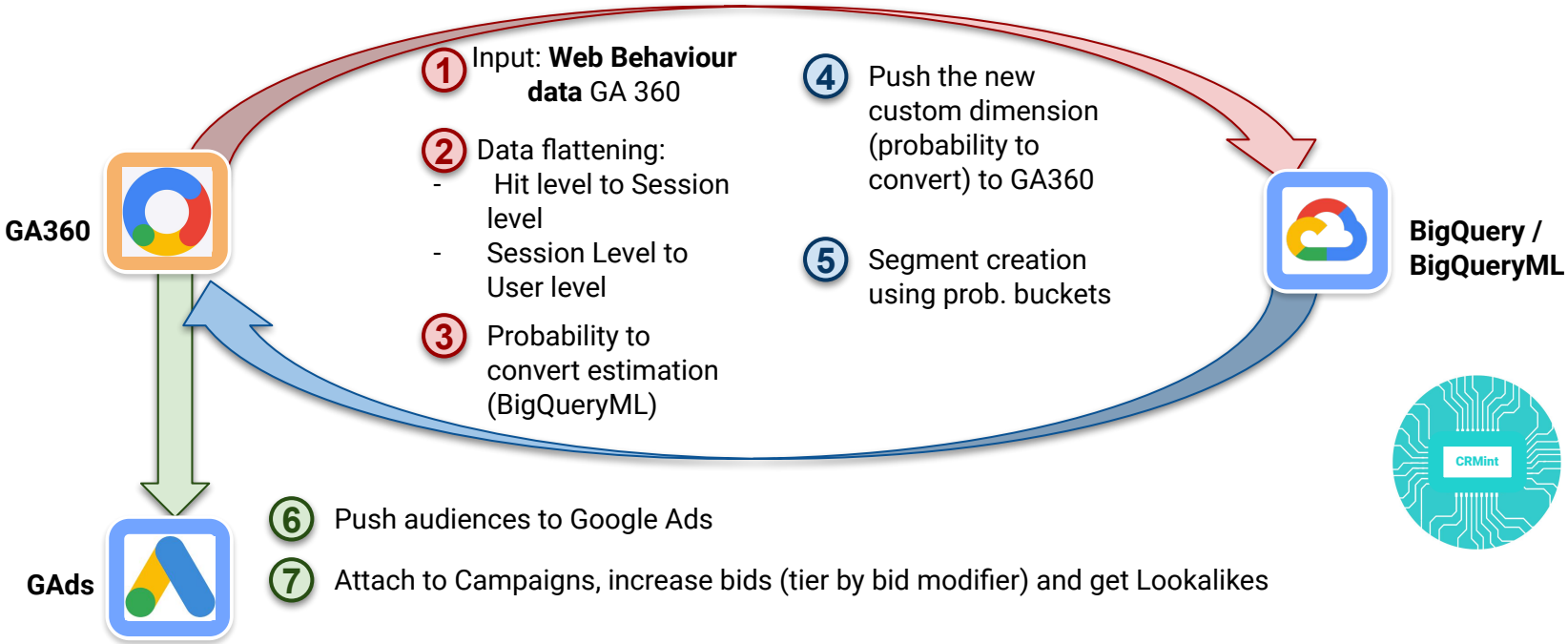
2. Tailor the message for high value customers

3. Find users similar to high value customers, using the power of Google Audiences

‘Iberia ML to predict users probability to convert with BQML‘ - (link)

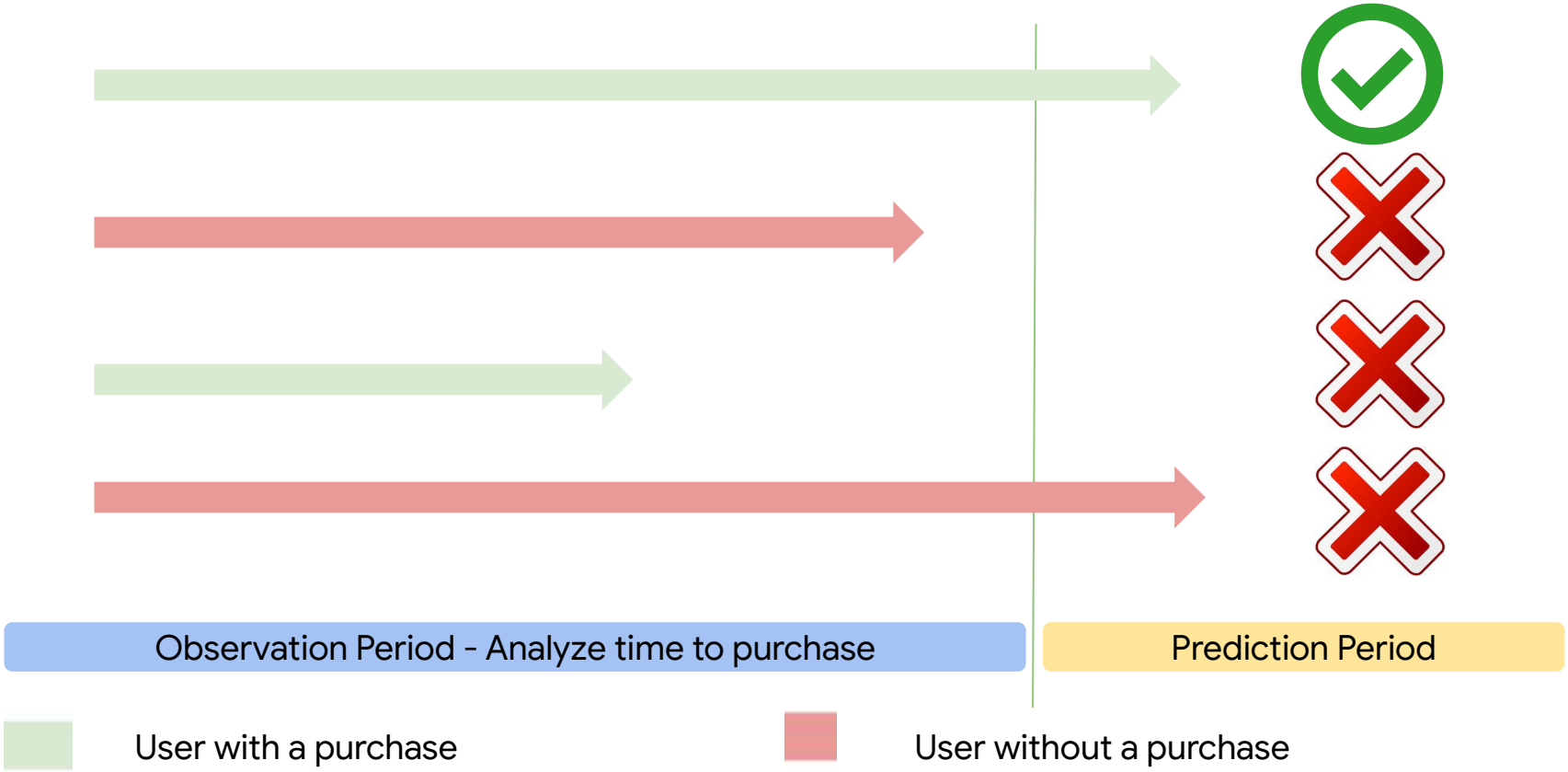
Iberia, in collaboration with Gauss & Neumann and Google, analyzes the browsing data of web users, available in Google Analytics 360 and dumped in BigQuery , using an algorithm adapted to their business model and developed in BigQuery Machine Learning , which predicts both the probability of conversion, as the estimated transaction value.

Architecture - ‘**BQML & CRMint as factors of time to market reduction**‘



Note: For the sake of simplicity, CRMInt is not showed, but it’s the central piece in the automatization of this process.

Model design - ‘**Keep calm and let the data talk**‘



Model design - ‘**Keep calm and let the business talk**‘

Consideration

-Custom Dimensions extracted from business are strong predictors of the outcome
- Feature cross make a huge difference in linear models (logistic regression) - be careful with overfitting

Extraction

-Make sure the you are capturing accurate data
- Use as much training volume as you can (include all month data, in different timeFrames, if not enough transactions use micro - conversions)

Analysis

- Avoid Signals correlated (to avoid colineality and improve explainability of the model)
-Avoid Signals that do not affect the model
-Use strategy for nulls (Imputation)
-Bucketize features to avoid outliers)

Modelization

-Use Regularization parameters (L1,L2)
-Use different hyperparameters (learn rate)
- Separate Training, evaluation, test data

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Break (🎉🎉)

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Fin (🎉🎉)

Hackathon Overview

01 Data Transformation in BigQuery GA 360

02 Train model through BigQueryML

03 Evaluate Model with BigQueryML

04 Test the model through BigQuery

05 Put into production with CRM int

Hackathon Overview

01 Data Transformation in BigQuery GA 360

02 Train model through BigQueryML

03 Evaluate Model with BigQueryML

04 Test the model through BigQuery

05 Put into production

1. Data Transformation- ‘**From Hit to User level**‘

```
----------------------DATA TRANSFORMATION-----------------

with prediction_dates as (select date from `bigquery-public-data.google_analytics_sample.ga_sessions_*` where geoNetwork.country = "United States"   and
_TABLE_SUFFIX BETWEEN '20170601' AND '20170615' group by 1),          observation_dates as (select date from `bigquery-public-
data.google_analytics_sample.ga_sessions_*` where geoNetwork.country = "United States"   and _TABLE_SUFFIX BETWEEN '20170501' AND '20170531'  group by
1),       prediction_transactions as ( select fullvisitorId as idtran from `bigquery-public-data.google_analytics_sample.ga_sessions_*` where
geoNetwork.country = "United States"   and _TABLE_SUFFIX BETWEEN '20170601' AND '20170615' and date in (select date from prediction_dates) and
totals.transactions >= 1   -- and fullvisitorid in (select id from ids_more_visits)
      group by 1),
     basetable as (
          select * from       `bigquery-public-data.google_analytics_sample.ga_sessions_*` where geoNetwork.country = "United States"   and
_TABLE_SUFFIX BETWEEN '20170501' AND '20170531' and date in (select date from observation_dates)  -- and fullvisitorid in (select id from
ids_more_visits)
      ),
     lastday as ( select date from observation_dates group by 1 order by 1 desc limit 1 ),
     last2day as ( select date from observation_dates group by 1 order by 1 desc limit 2 ),
     last7day as ( select date from observation_dates group by 1 order by 1 desc  limit 7 ),
     last15day as ( select date from observation_dates group by 1 order by 1 desc  limit 15 ),
     source_table as (
         select concat(cast(visitStarttime as string),
         cast(fullvisitorId as string)) as id,
         date,
         visitStarttime,
         fullvisitorId,
         totals.pageviews,
         totals.timeOnsite,
         totals.transactions,
         totals.sessionQualityDim,
         device.operatingSystem,
         device.browser,
         device.deviceCategory,
         channelGrouping from basetable,
         unnest(hits) as hit
--where fullvisitorId --not in (select idobs from observation_transactions )
group by 1,2,3,4,5,6,7,8,9,10,11,12)
```

Hackathon Overview

01 Data Transformation in BigQuery GA 360

02 Train model through BigQueryML

03 Evaluate Model with BigQueryML

04 Test the model through BigQuery

05 Put into production

2. Model Training- ‘**Train a model with transformed data**‘

```
CREATE OR REPLACE MODEL `PARTNER_TRAINING.sample_model_1year_v2`
OPTIONS(model_type='logistic_reg',
learn_rate_strategy='constant',
--learn_rate_strategy='line_search',
data_split_method= 'random',
data_split_eval_fraction = 0.15,
learn_rate= 0.6,
l1_reg=0.15,
auto_class_weights = true
) AS
SELECT
  device,
  OS,
  visits,
  visits_lastday,
  visits_last2day,
  visits_last7day,
  pageviews,
  pageviews_lastday,
  pageviews_last2day,
  pageviews_last7day,
  pagedepth,
  pagedepth_lastday,
  pagedepth_last2day,
  pagedepth_last7day,
  avg_SQ,
  max_SQ,
  avg_QS_lastday,
  avg_QS_last2day,
  avg_QS_last7day,
  max_QS_lastday,
  max_QS_last2day,
  max_QS_last7day,
  max_timeOnSite,
  max_timeOnSite_lastday,
  max_timeOnSite_last2day,
  max_timeOnSite_last7day,
  avg_timeOnSite_lastday,
  avg_timeOnSite_last2day,
  avg_timeOnSite_last7day,
```

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3. Evaluate the model- ‘**ok... but is my model good?**‘

sample_model_1year_v2

Details | Training | Evaluation | Schema

Aggregate metrics

Threshold	0.5000
Precision	0.0187
Recall	0.7183
Accuracy	0.8255
F1 score	0.0365
Log loss	0.5245
ROC AUC	0.8423

Score threshold

Positive class threshold 0.5065

Precision	0.0190
Recall	0.7042

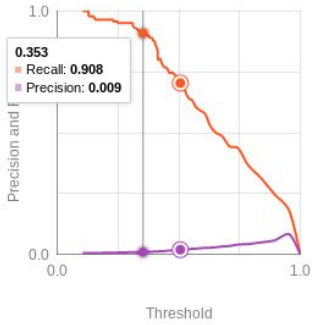
Use this slider above to see which score threshold works best for your model.

Confusion matrix

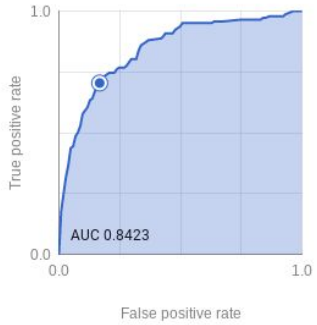
Actual labels \ Predicted labels	Positive	Negative
Positive	70.42%	29.58%
Negative	16.76%	83.24%

Precision-Recall curve

Precision and Recall vs Threshold



ROC curve



Evaluate the model- ‘**ok… but is my model good?**‘

What are the weights of the model?

Categorical Variables

1	device	*null*	mobile	-0.6155886202312307
			tablet	-0.5900274731026636
			desktop	-0.05134029618402976
2	OS	*null*	Firefox OS	-0.3053143590223346
			Macintosh	0.3131824993832482
			Windows	-0.46318863608673144
			Samsung	-0.630697200703975
			(not set)	-0.8567187773904958
			Xbox	-0.8808040886937785
			Nintendo WiiU	-0.5661990188855418
			Android	-0.6416918546062974
			Chrome OS	0.145032012028166
			SunOS	-0.22136673673976623

Numerical Variables

visits	0.1949046354916802
visits_lastday	0.07850133858974218
visits_last2day	0.09740174861823442
visits_last7day	0.17540645382491488
pageviews	0.017399601722247648
pageviews_lastday	0.012125817223498321
pageviews_last2day	0.012985186854796061
pageviews_last7day	0.013371970147292253
pagedepth	0.023689508651841624
pagedepth_lastday	0.0015114166616272753
pagedepth_last2day	0.004517319861942276
pagedepth_last7day	0.01582458947055531

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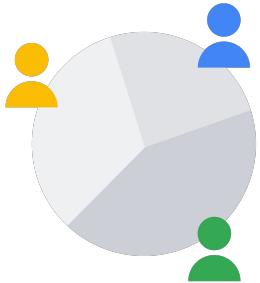
4. Test the model- ‘**ok… but is my model generalizing?**‘



```
SELECT
  clientId,predicted_label,label
FROM
  ml.PREDICT(MODEL `google.com:travel-dashboards.PARTNER_TRAINING.sample_model_1year_v2`, (
SELECT
  *
FROM
  `google.com:travel-dashboards.PARTNER_TRAINING.20170601` )
  )--where label = 1
```

Evaluate the model- ‘**ok… but is my model good?**‘

ROC Recall Vs false positive rate

		PREDICTION	
		Pos	**Neg**
ACTUAL	**Pos**	44	26
	Neg	2,487	13,443

$$\text{lift} = \frac{(TP/(TP+FP)}{(TP+FN)/(TP+TN+FP+FN)}$$

Positive observations 16%

Precision	2%
Recall	63%
Accuracy	84%
Total Lift	3.97

Hackathon Overview

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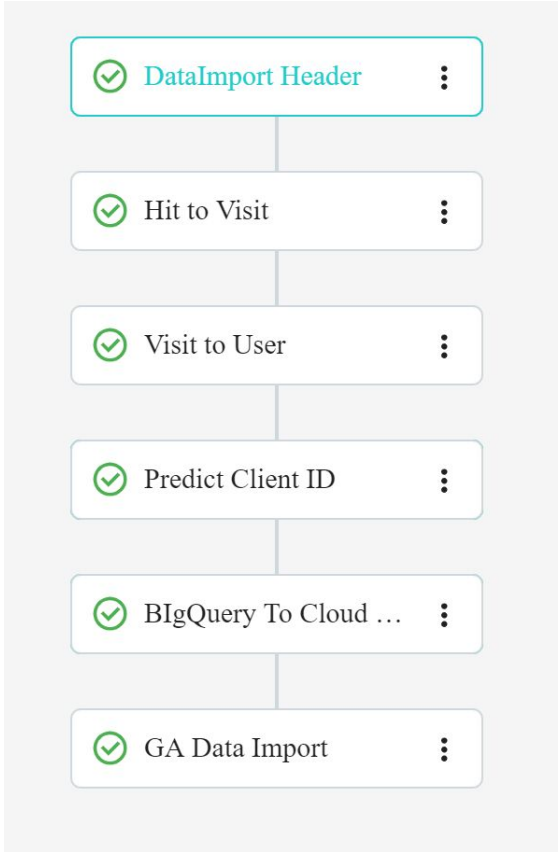
5. Put into production- ‘**Let CRMint do the work for you**‘

5. Put into production- ‘**Deploy CRM int**‘

Link

5. Put into production- ‘**Create a Pipeline for audiences**‘



Create an empty table to simulate required fields in Data Import -
BQ Launcher

Transform observation data of the last 30 days from hit to visit
BQ Launcher

Transform observation data of the last 30 days from Visit to Hit
BQ Launcher

Launch the ML predict to guess probabilities by clientId
BQ Launcher

Create a CSV from BQ to Cloud Storage (eliminating Headers)
BQ to Cloud Storage

Create a Data Import
Cloud Storage to Data Import

Thank you!