Building Better Models In the SAP Analytics Cloud

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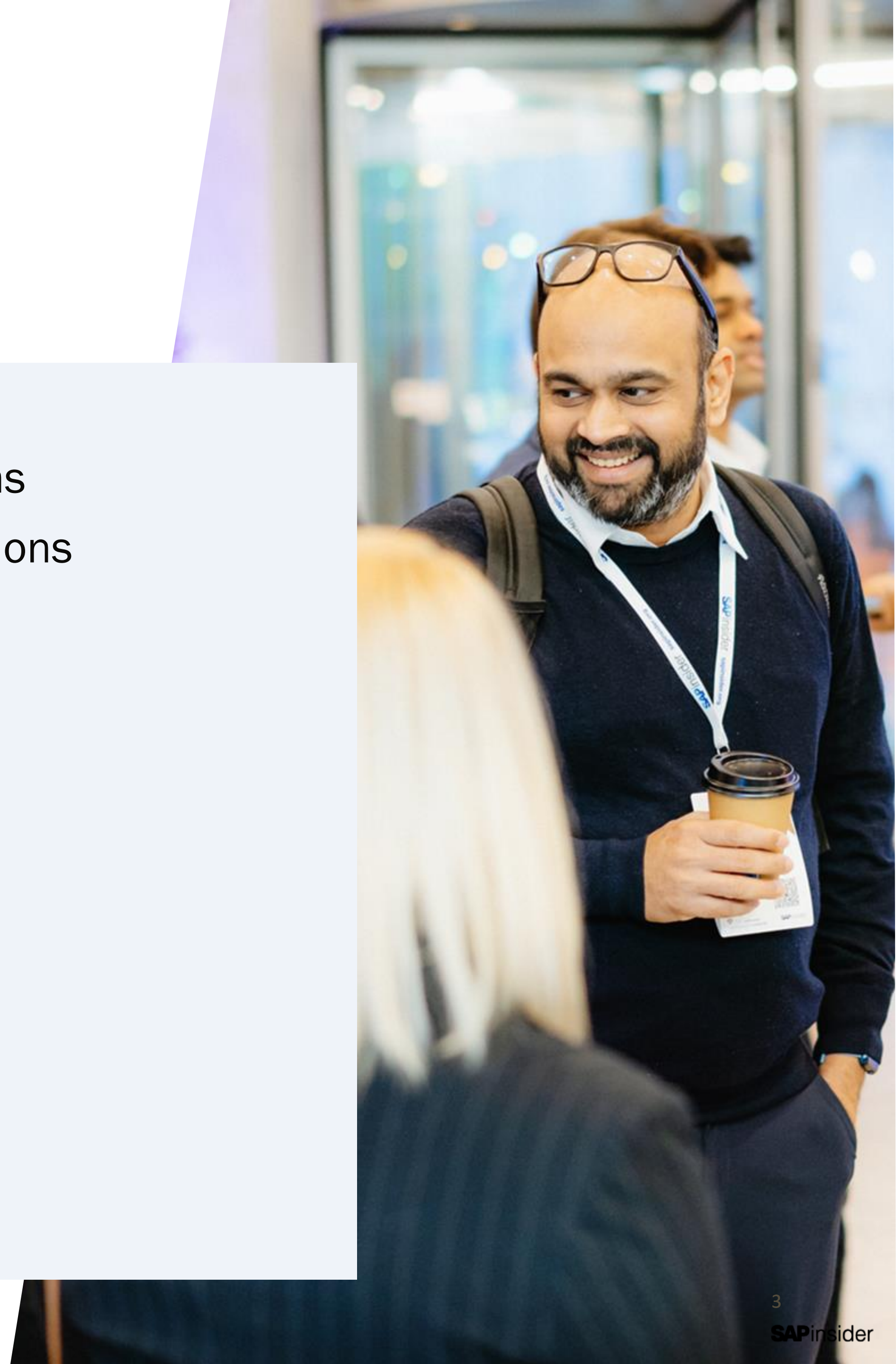
In This Session

This is a technical session best suited for SAC model developers. It’s easy to learn how to use features through SAC documentation and videos provided by SAP. So, instead of focusing on how to use specific features of SAC, this presentation will focus on model building <u>methodology</u> that you won’t find in any manual or documentation.

There will be some sql examples near the end of the presentation. It is recommended to download this presentation to remember the sql examples.

What We'll Cover

- The two SaaS analytic tool modeling paradigms
- Acquiring data (import) vs Live Query Connections
- The concept of dimensionality
- Tips for creating aggregated data sets from transactional data
- Wrap-Up

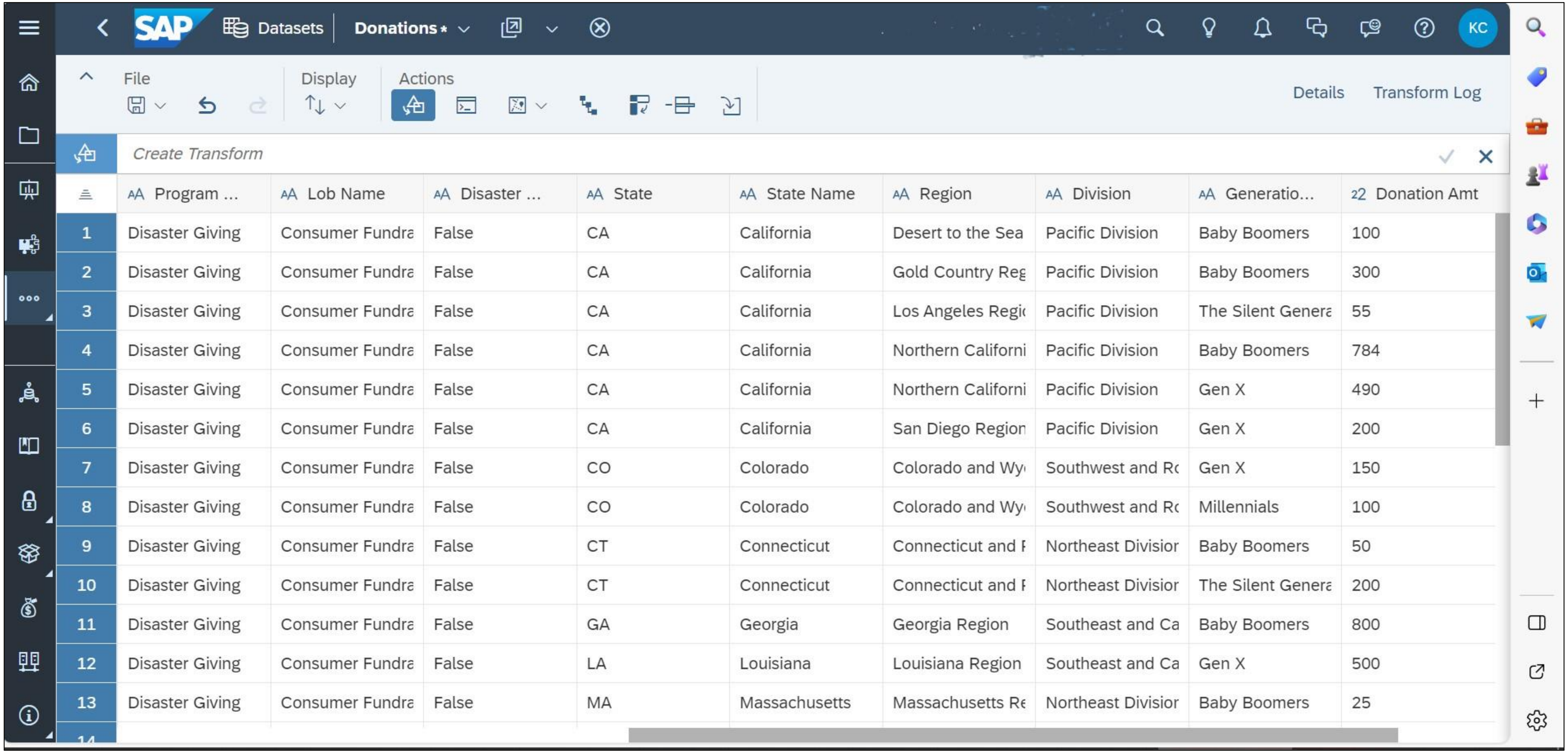


The two SaaS Analytic Tool Modeling Paradigms

Models based on:

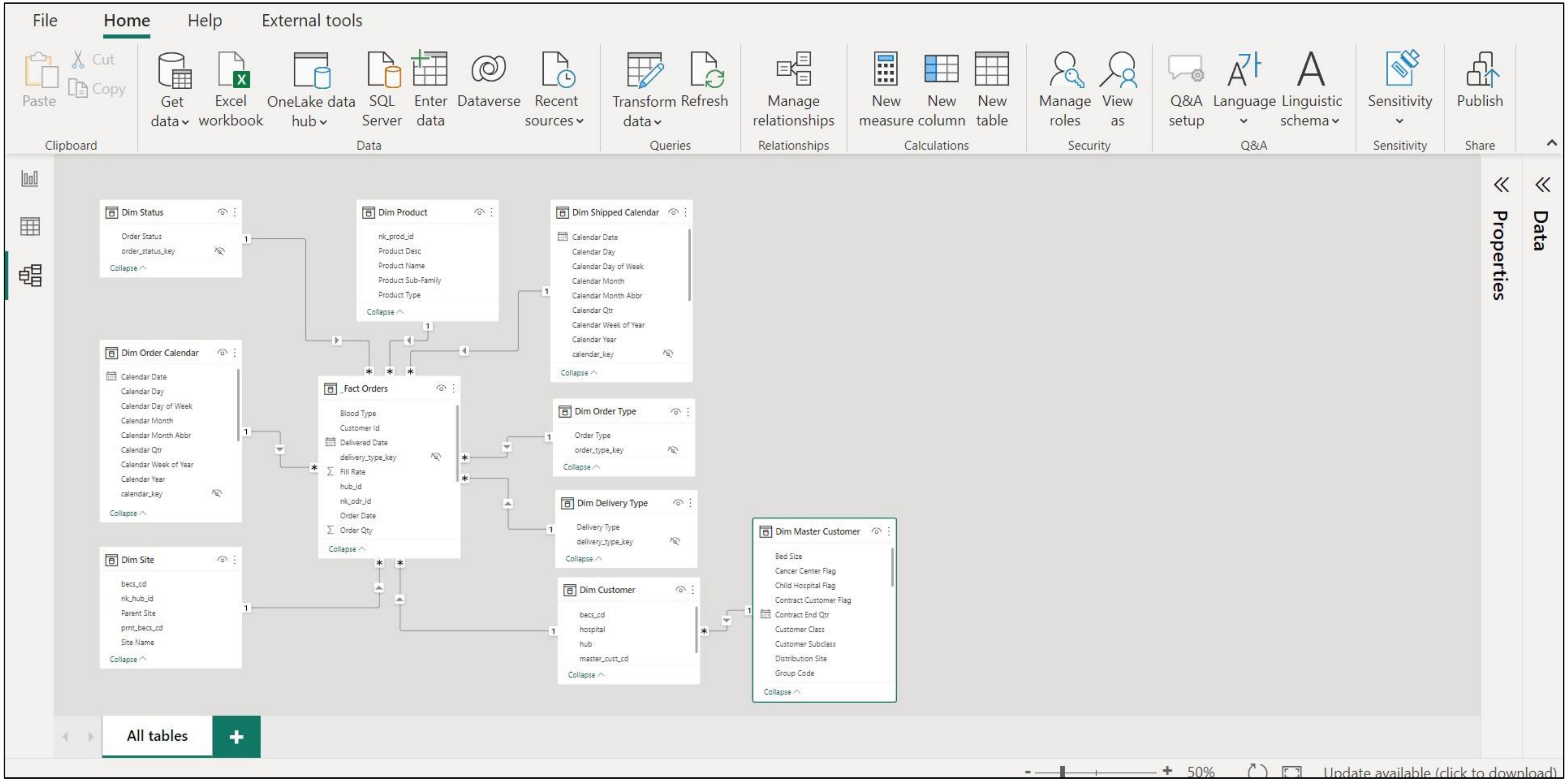
1. Flattened Mergeable Tables like SAC
2. Entity Relationship (Dimension Model/Star Schema) like some other SaaS Analytic tools

SAC Dataset – One flattened Mergeable table



	Program ...	Lob Name	Disaster ...	State	State Name	Region	Division	Generatio...	Donation Amt
1	Disaster Giving	Consumer Fundra	False	CA	California	Desert to the Sea	Pacific Division	Baby Boomers	100
2	Disaster Giving	Consumer Fundra	False	CA	California	Gold Country Reg	Pacific Division	Baby Boomers	300
3	Disaster Giving	Consumer Fundra	False	CA	California	Los Angeles Regi	Pacific Division	The Silent Genera	55
4	Disaster Giving	Consumer Fundra	False	CA	California	Northern Californi	Pacific Division	Baby Boomers	784
5	Disaster Giving	Consumer Fundra	False	CA	California	Northern Californi	Pacific Division	Gen X	490
6	Disaster Giving	Consumer Fundra	False	CA	California	San Diego Region	Pacific Division	Gen X	200
7	Disaster Giving	Consumer Fundra	False	CO	Colorado	Colorado and Wy	Southwest and Ro	Gen X	150
8	Disaster Giving	Consumer Fundra	False	CO	Colorado	Colorado and Wy	Southwest and Ro	Millennials	100
9	Disaster Giving	Consumer Fundra	False	CT	Connecticut	Connecticut and F	Northeast Divisior	Baby Boomers	50
10	Disaster Giving	Consumer Fundra	False	CT	Connecticut	Connecticut and F	Northeast Divisior	The Silent Genera	200
11	Disaster Giving	Consumer Fundra	False	GA	Georgia	Georgia Region	Southeast and Ca	Baby Boomers	800
12	Disaster Giving	Consumer Fundra	False	LA	Louisiana	Louisiana Region	Southeast and Ca	Gen X	500
13	Disaster Giving	Consumer Fundra	False	MA	Massachusetts	Massachusetts Re	Northeast Divisior	Baby Boomers	25

Competitor Dataset - Entity Relationship (Dimensional Model)



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A Deeper Look Into the Two Different Modeling Paradigms

- Entity Relationship Models are based on joining tables together – preferably in a star schema
- SAC models and datasets are based on single datasets that can be merged

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- SAC models and datasets are based on single datasets that can be merged
  - Augmented analytics features such as Smart Insight, Search to Insight, Predictive and Data Explorer are all possible because of one large dataset in the models
  - Allows for mergeable datasets on common dimensions from different sources

A Deeper Look Into the Two Different Modeling Paradigms

Gartner:

"The real action in the BI market is around augmented analytics, or how well the BI tools incorporate machine learning and AI."

Acquiring data (Importing) vs Live Query Connections

With most data sources the important functionality of SAC is lost using Live Query. For this reason, acquiring data is the greatly preferred method for building stories in SAC.

It is important in most cases to build models that are efficiently designed around acquiring data.

Importing vs Live Query Connections from SAP blog

Live vs Import Connection Support Matrix

This is a comparison table outlining the supported features for Live and Import connections in SAP Analytics Cloud;

Features	Live Connection	Import Connection
Data Wrangling / Preparation	X	✓
Smart Insights	SAP HANA	✓
Smart Discovery	X	✓
Smart Predict	SAP HANA	✓
Time Series Forecasting	✓	✓
Calculated Dimension	X	✓
Data Security and Privacy	Handled in backend	Handled in SAC Model
Planning	SAP BPC	Planning Models
Data Scheduling	Real-time Data	✓

Live Query connections are used by traditional reporting tools like SAP Business Objects

- Most data sources used for operational, or ad-hoc reporting are complex in nature
  - This requires dynamic sql building by the BI tool and one reason why Business Objects is a preferred tool for operational reporting
  - SAC hybrid can use a Business Objects universe as a data source and can build dynamic sql with some limitations

The Concept of Dimensionality

There is exponential growth of row count as dimensions are added to a data set. This is particularly important to understand since acquiring data is preferred for model building

Understanding the theme of your story will help to greatly reduce row count by:

- Identifying the core dimensions of the theme or logical dimensional groupings
- Building small datasets with the core dimensions of the theme
- Merging the datasets

Why the Concept of Dimensionality is Important

- The dimension count in a dataset has a much greater effect on row count than most people understand
- SAC, like most SaaS analytic tools, work best when data is acquired (imported)
  - As seen from the previous section most of the SAC features are lost when using live query from non-SAP data sources
  - There is (supposedly) a limit of 100,000,000 rows in SAC but smaller dataset function better in an SAC model

Example – How Dimensionality Affects Row Count

Simple data set with 5 dimensions
you might find in a product demo

Columns: On-line Store Data Set	Number of Dimension Values
Year	3
Month	12
Product Group & Product	30
Customer Type	6
Division & State	52
Revenue	0

336,960 Rows

Example – How Dimensionality Affects Row Count

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Product Group & Product	30
Customer Type	6
Division & State	52
Revenue	0

336,960 Rows

Add 2 demographic dimensions Race & Gender

Columns: On-line Store Data Set	Number of Dimension Values
Year	3
Month	12
Product Group & Product	30
Customer Type	6
Division & State	52
Gender	3
Race	7
Revenue	0

7,076,160 Rows

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Year	3
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336,960 Rows

Add 2 demographic dimensions Race & Gender

Columns: On-line Store Data Set	Number of Dimension Values
Year	3
Month	12
Product Group & Product	30
Customer Type	6
Division & State	52
Gender	3
Race	7
Revenue	0

7,076,160 Rows

Add just one more demographic dimension – Age Band

Columns: On-line Store Data Set	Number of Dimension Values
Year	3
Month	12
Product Group & Product	30
Customer Type	6
Division & State	52
Gender	3
Race	7
Age Band	12
Revenue	0

84,913,920 Rows

Solution – Reducing Row Count

Original Query w/ 8 Dimensions

Single Query Columns	Dimension Values
Year	3
Month	12
Product Group & Product	30
Customer Type	6
Division & State	52
Gender	3
Race	7
Age Band	12
Total Rows	**84,913,920**

Create Separate Queries & Datasets Based On Logical Dimension Groups or Theme

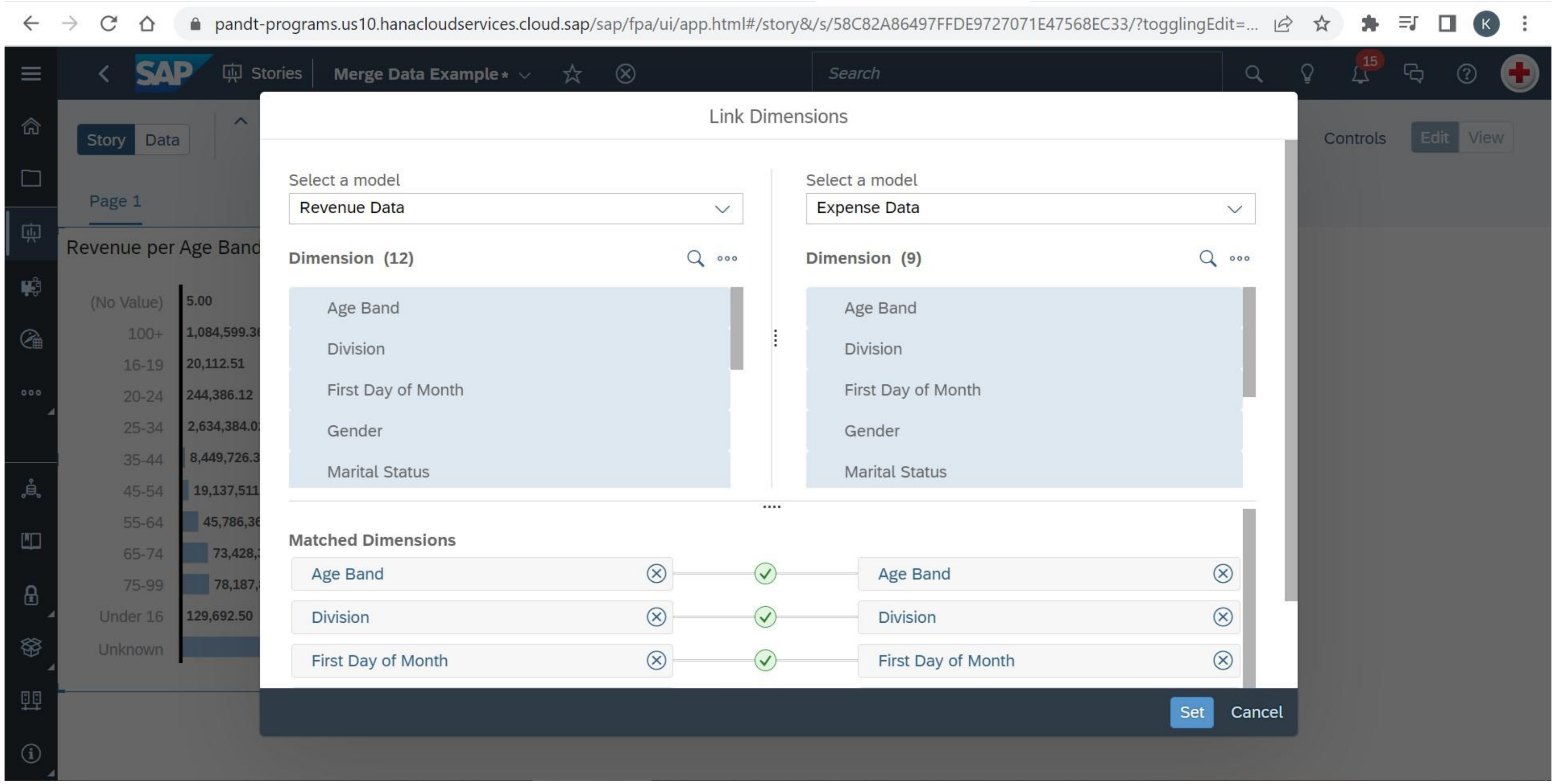
Total row count reduced from 84,913,920 to a total of 67,536
The 3 Queries will be merged in the story by the Common Demographic Dimensions

Geography & Demographics	Dimension Values
Division & State	52
Gender	3
Race	7
Age Band	12
Total Rows	**13,104**

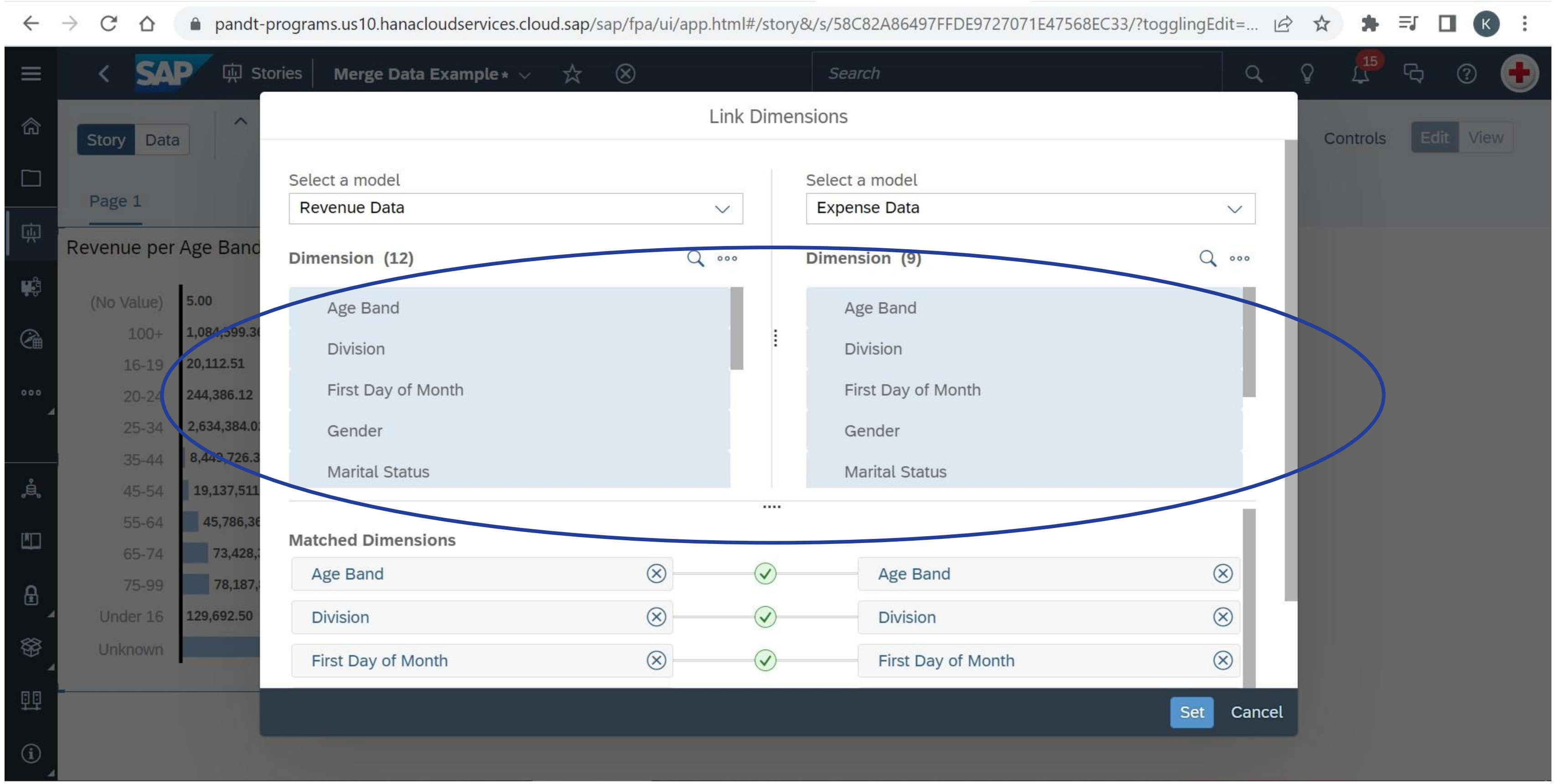
Time & Demographics	Dimension Values
Year	3
Month	12
Gender	3
Race	7
Age Band	12
Total Rows	**9,072**

Product & Customer Demographics	Dimension Values
Product Group & Product	30
Customer Type	6
Gender	3
Race	7
Age Band	12
Total Rows	**45,360**

Example - Using Merged Datasets in an SAC Story

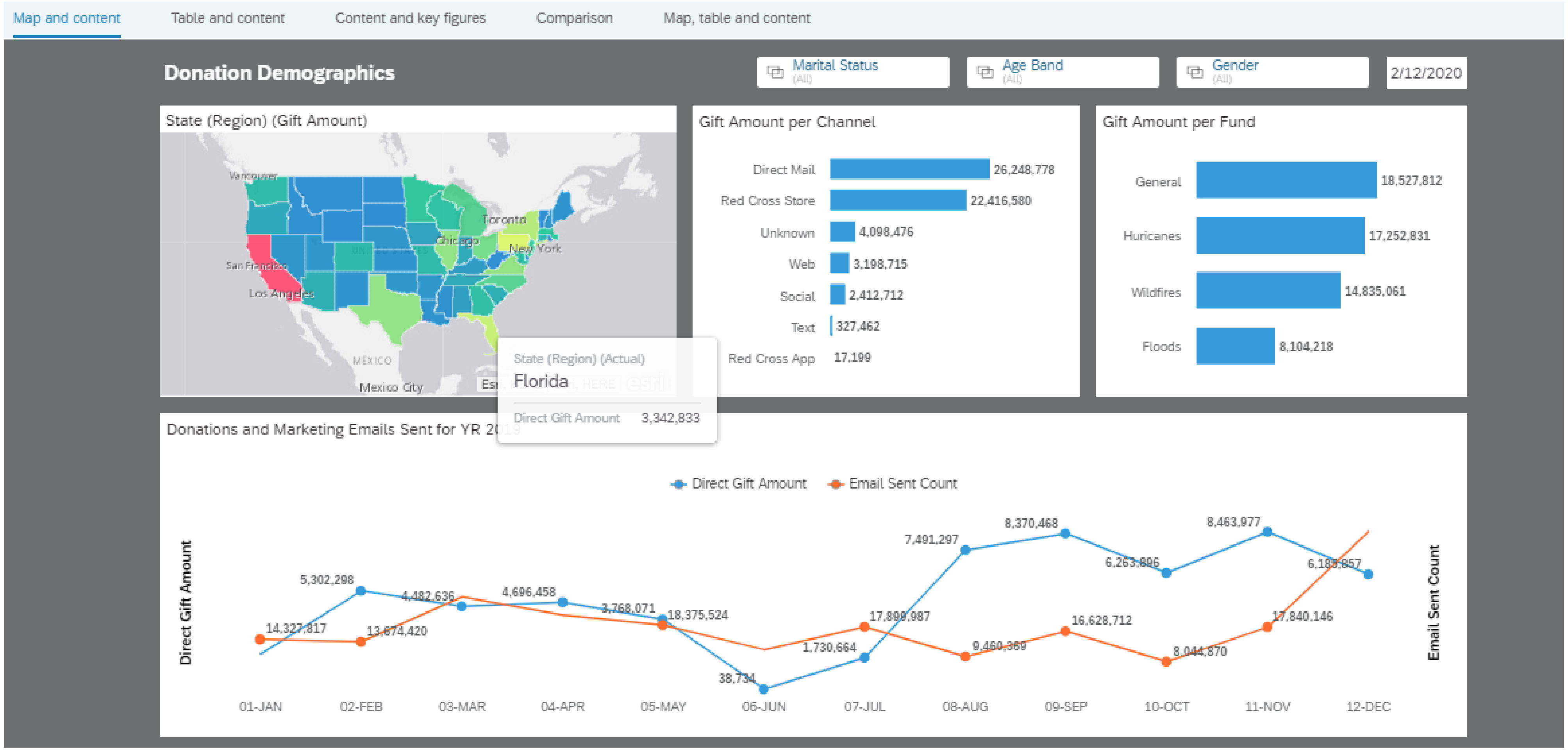


Example - Using Merged Datasets in an SAC Story



Example - Using Merged Datasets in an SAC Story

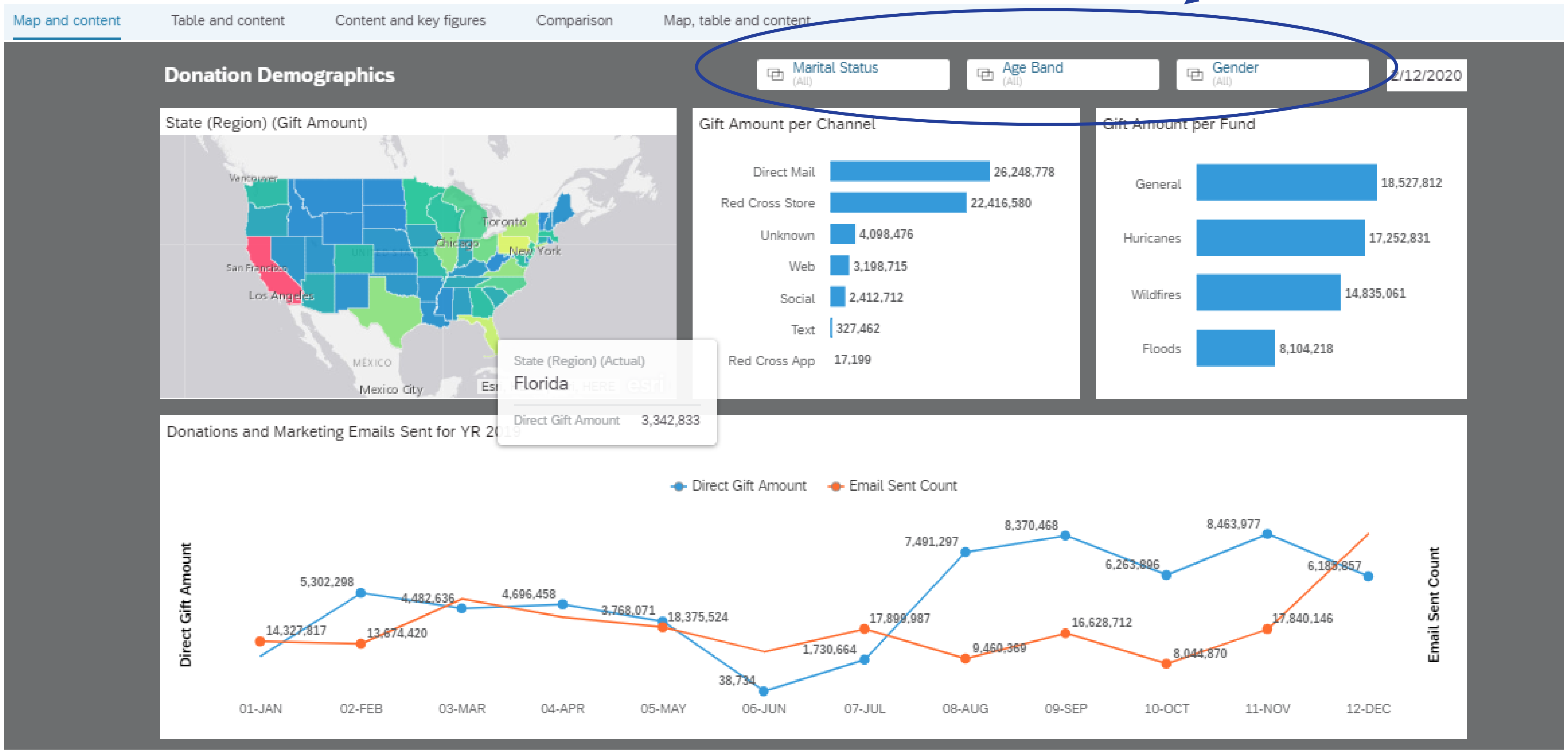
In this example each Chart is built from one dataset



Example - Using Merged Datasets in an SAC Story

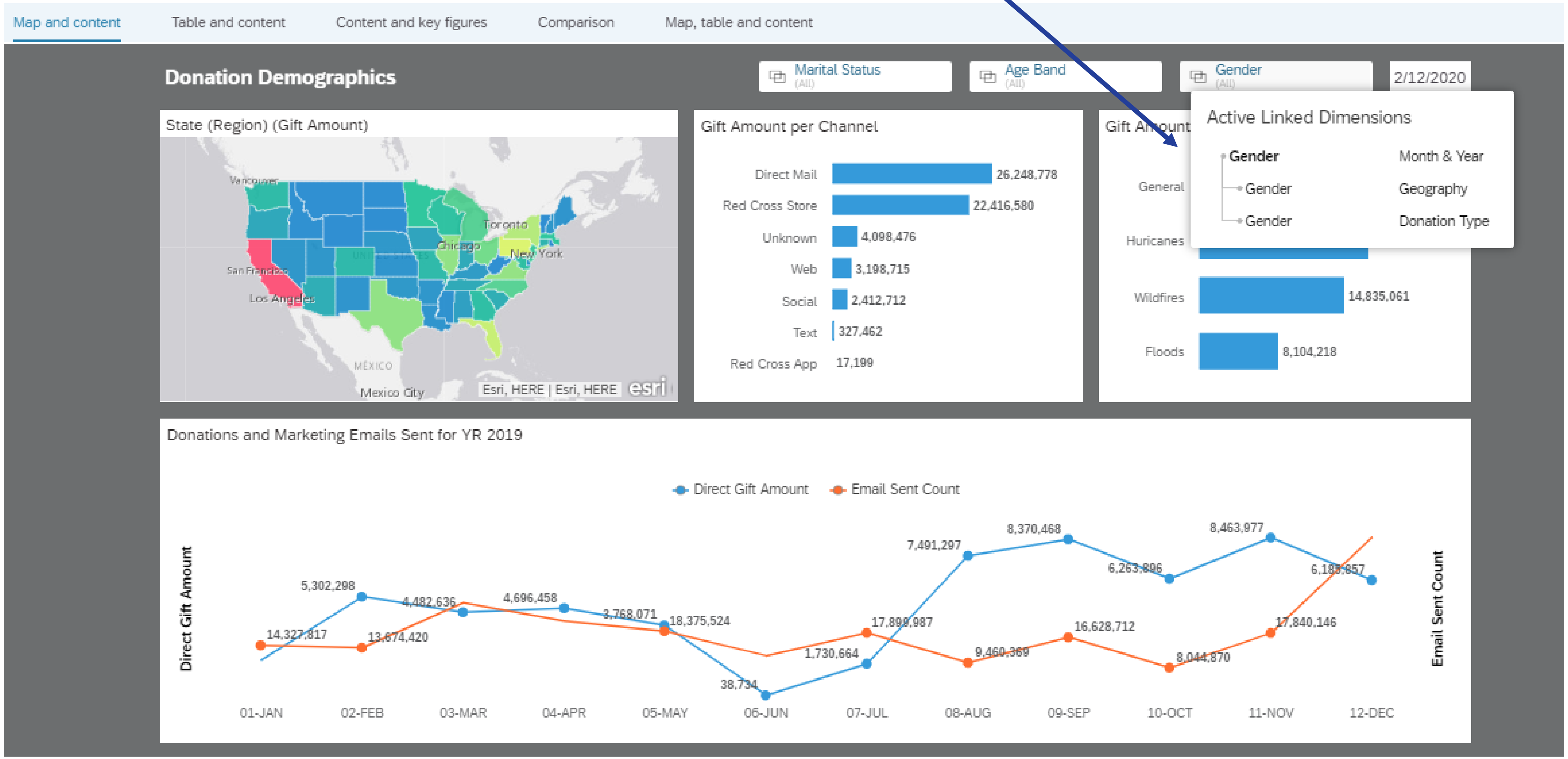
In this example each Chart is built from one dataset

There is an input control (filter)for each of the demographic dimensions.



Example - Using Merged Datasets in an SAC Story

There is an input control for each demographic shared by each model/dataset. Clicking the link indicator icon displays the datasets that are linked.



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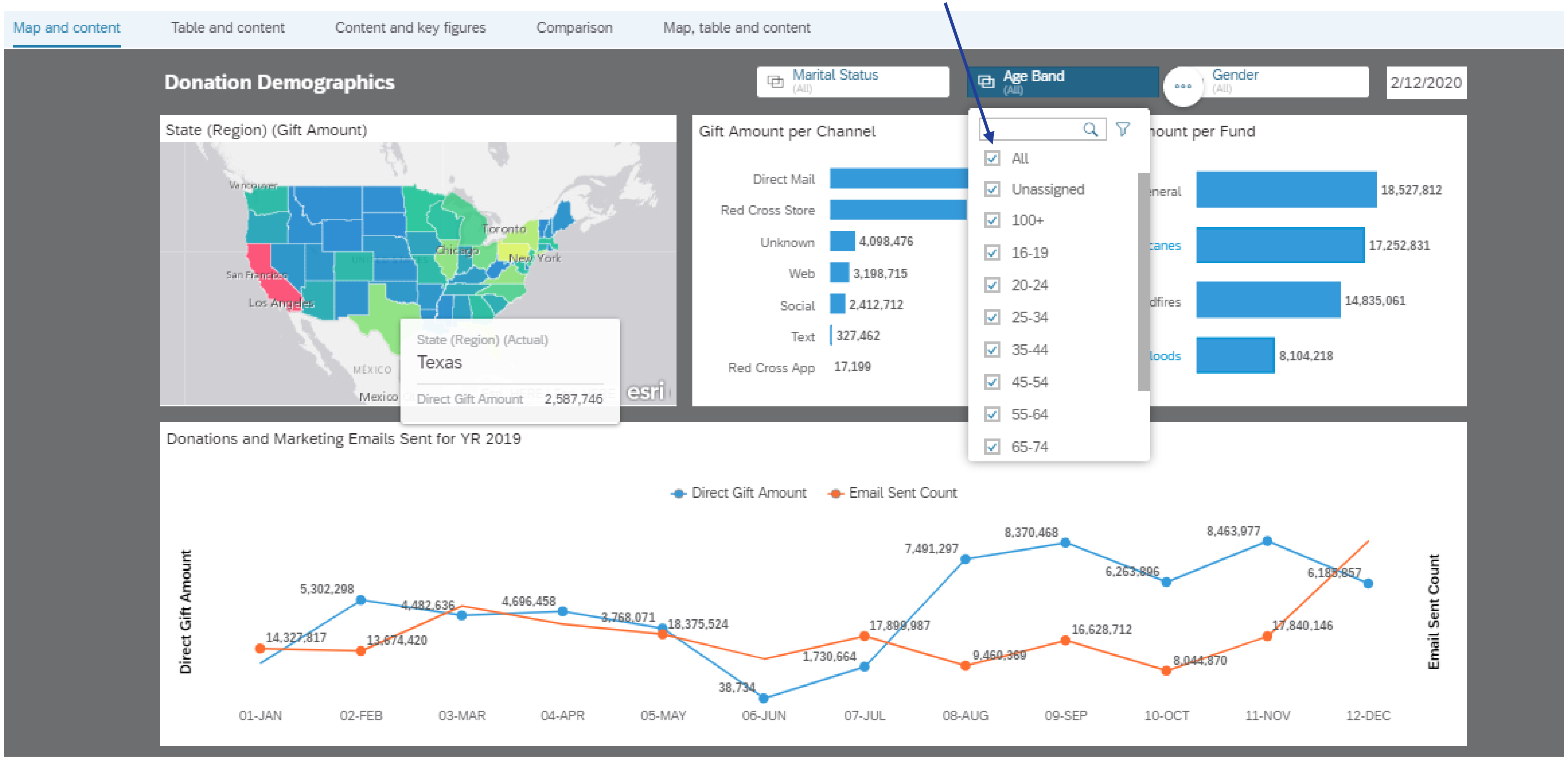
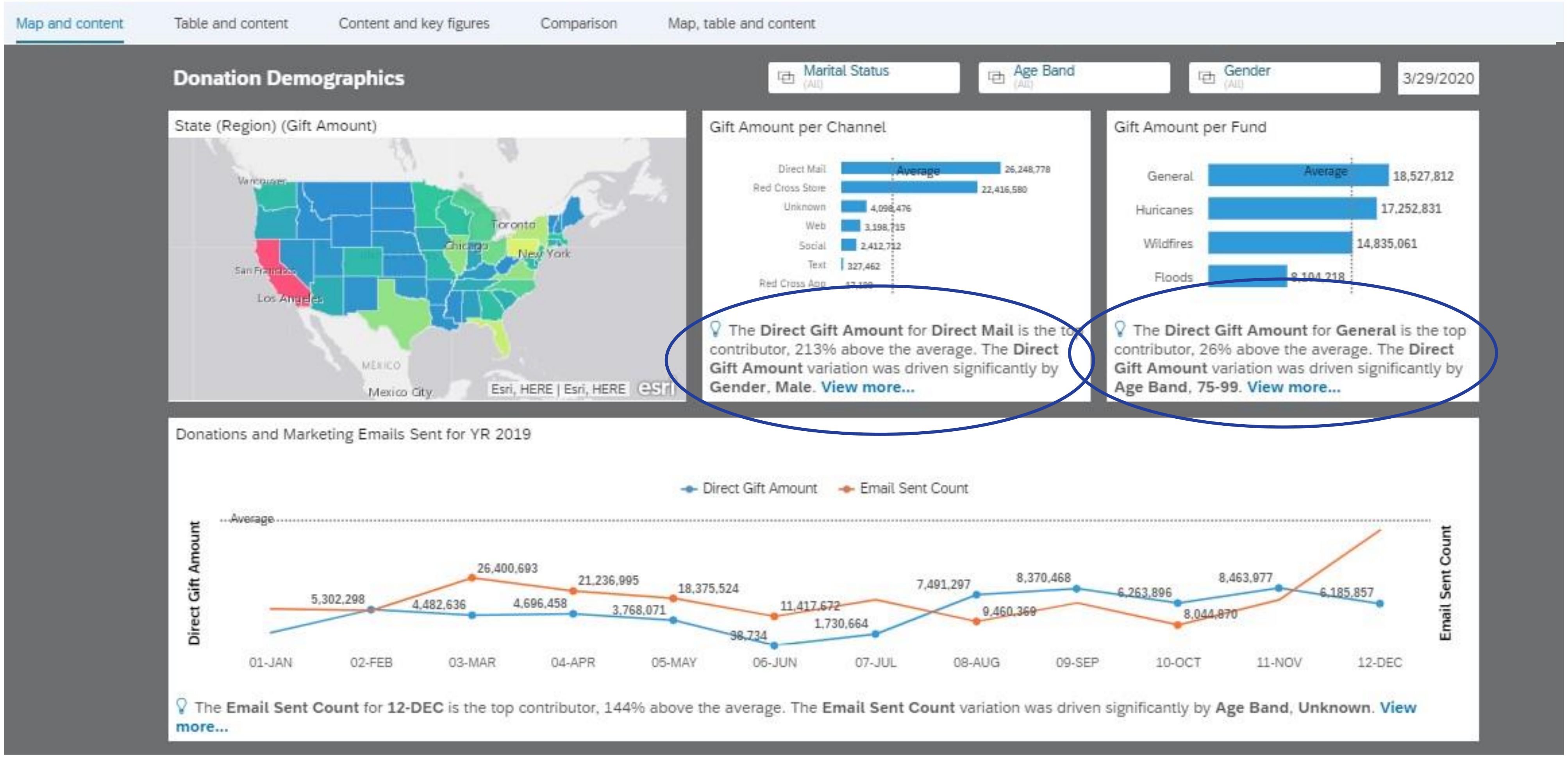
Example - Using Merged Datasets in an SAC Story

Since Models are merged, the Input Controls will filter charts built from different data sets or models



Example - Using Merged Datasets in an SAC Story

Smart Insights can be added to determine values of the 3 demographics influenced each chart



Key Points – Dimensionality of Data in SAC

- SAC allows 100 million rows but there is a cost to large data sets
  - Load time
  - SAC resources
  - Difficulty debugging data quality errors
- Generally, stories have a theme
  - The theme helps determine dimension groups
  - You can merge data sets along common dimensions in a story
- Common dimensions in the models can be used to filter all datasets in a story
- Smart Insights will still work when merging dimension
- Data Explorer can still be used within each data set

Tips for creating aggregated data sets from transactional data

Typically, most dashboards do not look at transactional data which contains too much detail for analytical reporting. Aggregate datasets generally more useful for building SAC stories or any analytic dashboard.

Creating aggregate datasets is not a simple process. It requires many transformations that must be done using sql to keep row count low.

Building Aggregate Datasets

Creating aggregate datasets is an essential part of data architecture for self-service or any dashboard development. The basic steps to create an aggregation table from a fact table in a dimensional model or transactional dataset are:

- Remove from fact table's granular transactional columns
  - A rule of thumb those columns will generally be:
    - Person, company or organization keys
    - Transaction date or key
    - Geography (i.e., address)
- Replace transactional columns with attributes of the dimensions
  - Typically, these might be:
    - Week or Month & year of the transaction date or first day of the month
    - U.S. State or zip code of the geography
    - Attribute of a person (for instance age)
    - Grouping of any attribute (for instance age band derived from age)

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An actual date is required to build timeline charts in an SAC story. It is a better option than month & year dimensions.

Transactional dataset example

Full Name	Birth Date	Donation Date	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
Peter Jones	02/01/52	12/28/23	54220	California Wildfires	M	M	Married	Caucasian	50
Kent Smith	02/01/51	12/29/23	70001	California Wildfires	M	M	Married	Caucasian	100
Russel Garret	02/01/42	12/27/23	18444	California Wildfires	M	M	Married	Caucasian	0
Jonathon Mann	06/01/64	12/24/23	01460	International	F	M	Married	Caucasian	0
Deirdra Thomas	07/24/44	12/27/23	37013	Disaster Relief	M	M	Married	Caucasian	100
Britt Collins	05/21/40	12/29/23	49046	Disaster Relief	M	M	Married	Caucasian	19
Colin Parker	02/01/37	12/21/23	95404	Disaster Relief	U	M	Married	Caucasian	19
Ward Cooper	04/02/44	12/27/23	29418	Disaster Relief	F	M	Married	Black or African-American	100
Mary Anne Hardy	10/01/57	12/29/23	44606	California Wildfires	M	M	Married	Caucasian	40
Phil Ludwig	03/01/43	12/26/23	37209	Disaster Relief	F	M	Married	Caucasian	20
Lawrence Patton	09/01/87	12/26/23	14526	California Wildfires	U	M	Married	Asian	25
Amanda Hampton	12/10/45	12/29/23	49442	Disaster Relief	F	S	Single	Black or African-American	20
Gerry Parks	03/08/35	12/22/23	59901	Disaster Relief	M	M	Married	Black or African-American	57
Cindy Chang	03/11/62	12/27/23	06483	Disaster Relief	M	M	Married	Asian	15
Gregory Holt	10/14/62	12/22/23	68506	Disaster Relief	F	M	Married	Caucasian	25
Jeff Kleiner	02/09/47	12/29/23	43213	Disaster Relief	M	M	Married	Caucasian	40
Edna Kim	08/04/53	12/26/23	44233	Disaster Relief	M	M	Married	Caucasian	100
Karl Leal	12/11/48	12/22/23	44149	Disaster Relief	F	S	Single	Caucasian	38
Cindy Maguire	12/01/38	12/26/23	08505	California Wildfires	M	M	Married	Caucasian	50
Michael Lee	11/13/46	12/26/23	67521	California Wildfires	F	M	Married	Asian	150
Julie Masek	12/10/65	12/22/23	12193	Disaster Relief	M	M	Married	Caucasian	25
Brett Merrick	11/23/46	12/26/23	28635	Disaster Relief	M	M	Married	Caucasian	50
Jack Mumford	11/01/40	12/26/23	19426	Disaster Relief	M	M	Married	Caucasian	30
Shelly Montgomery	02/14/57	12/22/23	48412	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Step 1 – Delete Person or Organization (or convert it to an attribute like person or org type)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Full Name	Birth Date	Donation Date	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount				
2	Peter Jones	02/01/52	12/28/23	54220	California Wildfires	M	M	Married	Caucasian	50				
3	Kent Smith	02/01/51	12/29/23	70001	California Wildfires	M	M	Married	Caucasian	100				
4	Russel Garret	02/01/42	12/27/23	18444	California Wildfires	M	M	Married	Caucasian	0				
5	Jonathon Mann	06/01/64	12/24/23	01460	International	F	M	Married	Caucasian	0				
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8	Colin Parker	02/01/37	12/21/23	95404	Disaster Relief	U	M	Married	Caucasian	19				
9	Ward Cooper	04/02/44	12/27/23	29418	Disaster Relief	F	M	Married	Black or African-American	100				
10	Mary Anne Hardy	10/01/57	12/29/23	44606	California Wildfires	M	M	Married	Caucasian	40				
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Query 1

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	Birth Date	Donation Date	Calendar Month	Calendar Year	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Zip 5	Donation Amount
2	02/01/52	12/28/23	12	2023	California Wildfires	M	M	Married	Caucasian	54220	50
3	02/01/51	12/29/23	12	2023	California Wildfires	M	M	Married	Caucasian	70001	100
4	02/01/42	12/27/23	12	2023	California Wildfires	M	M	Married	Caucasian	18444	0
5	06/01/64	12/24/23	12	2023	International	F	M	Married	Caucasian	01460	0
6	07/24/44	12/27/23	12	2023	Disaster Relief	M	M	Married	Caucasian	37013	100
7	05/21/40	12/29/23	12	2023	Disaster Relief	M	M	Married	Caucasian	49046	19
8	02/01/37	12/21/23	12	2023	Disaster Relief	U	M	Married	Caucasian	95404	19
9	04/02/44	12/27/23	12	2023	Disaster Relief	F	M	Married	Black or African-American	29418	100
10	10/01/57	12/29/23	12	2023	California Wildfires	M	M	Married	Caucasian	44606	40
11	03/01/43	12/26/23	12	2023	Disaster Relief	F	M	Married	Caucasian	37209	20
12	09/01/87	12/26/23	12	2023	California Wildfires	U	M	Married	Asian	14526	25
13	12/10/45	12/29/23	12	2023	Disaster Relief	F	S	Single	Black or African-American	49442	20
14	03/08/35	12/22/23	12	2023	Disaster Relief	M	M	Married	Black or African-American	59901	57
15	03/11/62	12/27/23	12	2023	Disaster Relief	M	M	Married	Asian	06483	15
16	10/14/62	12/22/23	12	2023	Disaster Relief	F	M	Married	Caucasian	68506	25
17	02/09/47	12/29/23	12	2023	Disaster Relief	M	M	Married	Caucasian	43213	40
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23	11/23/46	12/26/23	12	2023	Disaster Relief	M	M	Married	Caucasian	28635	50
24	11/01/40	12/26/23	12	2023	Disaster Relief	M	M	Married	Caucasian	19426	30
25	02/14/57	12/22/23	12	2023	Disaster Relief	F	M	Married	Caucasian	48412	25

Query 1

Step 2 – Birthdate is removed from sql after transforming it to age

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Birth Date	Age	Donation Date	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount					
2	02/01/52	71	12/28/23	54220	California Wildfires	M	M	Married	Caucasian	50					
3	02/01/51	72	12/29/23	70001	California Wildfires	M	M	Married	Caucasian	100					
4	02/01/42	81	12/27/23	18444	California Wildfires	M	M	Married	Caucasian	0					
5	06/01/64	59	12/24/23	01460	International	F	M	Married	Caucasian	0					
6	07/24/44	79	12/27/23	37013	Disaster Relief	M	M	Married	Caucasian	100					
7	05/21/40	83	12/29/23	49046	Disaster Relief	M	M	Married	Caucasian	19					
8	02/01/37	86	12/21/23	95404	Disaster Relief	U	M	Married	Caucasian	19					
9	04/02/44	79	12/27/23	29418	Disaster Relief	F	M	Married	Black or African-American	100					
10	10/01/57	66	12/29/23	44606	California Wildfires	M	M	Married	Caucasian	40					
11	03/01/43	80	12/26/23	37209	Disaster Relief	F	M	Married	Caucasian	20					
12	09/01/87	36	12/26/23	14526	California Wildfires	U	M	Married	Asian	25					
13	12/10/45	78	12/29/23	49442	Disaster Relief	F	S	Single	Black or African-American	20					
14	03/08/35	88	12/22/23	59901	Disaster Relief	M	M	Married	Black or African-American	57					
15	03/11/62	61	12/27/23	06483	Disaster Relief	M	M	Married	Asian	15					
16	10/14/62	61	12/22/23	68506	Disaster Relief	F	M	Married	Caucasian	25					
17	02/09/47	76	12/29/23	43213	Disaster Relief	M	M	Married	Caucasian	40					
18	08/04/53	70	12/26/23	44233	Disaster Relief	M	M	Married	Caucasian	100					
19	12/11/48	75	12/22/23	44149	Disaster Relief	F	S	Single	Caucasian	38					
20	12/01/38	85	12/26/23	08505	California Wildfires	M	M	Married	Caucasian	50					
21	11/13/46	77	12/26/23	67521	California Wildfires	F	M	Married	Asian	150					
22	12/10/65	58	12/22/23	12193	Disaster Relief	M	M	Married	Caucasian	25					
23	11/23/46	77	12/26/23	28635	Disaster Relief	M	M	Married	Caucasian	50					
24	11/01/40	83	12/26/23	19426	Disaster Relief	M	M	Married	Caucasian	30					
25	02/14/57	66	12/22/23	48412	Disaster Relief	F	M	Married	Caucasian	25					

Query 1

Step 2 – Birthdate is removed from sql after transforming it to age

	Birth Date	Age	Donation Date	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
2	02/01/52	71	12/28/23	54220	California Wildfires	M	M	Married	Caucasian	50
3	02/01/51	72	12/29/23	70001	California Wil					
4	02/01/42	81	12/27/23	18444	California Wil					
5	06/01/64	59	12/24/23	01460	International					
6	07/24/44	79	12/27/23	37013	Disaster Reli					
7	05/21/40	83	12/29/23	49046	Disaster Reli					
8	02/01/37	86	12/21/23	95404	Disaster Reli					
9	04/02/44	79	12/27/23	29418	Disaster Reli					
10	10/01/57	66	12/29/23	44606	California Wil					
11	03/01/43	80	12/26/23	37209	Disaster Reli					
12	09/01/87	36	12/26/23	14526	California Wil					
13	12/10/45	78	12/29/23	49442	Disaster Reli					
14	03/08/35	88	12/22/23	59901	Disaster Reli					
15	03/11/62	61	12/27/23	06483	Disaster Reli					
16	10/14/62	61	12/22/23	68506	Disaster Reli					
17	02/09/47	76	12/29/23	43213	Disaster Reli					
18	08/04/53	70	12/26/23	44233	Disaster Reli					
19	12/11/48	75	12/22/23	44149	Disaster Reli					
20	12/01/38	85	12/26/23	08505	California Wil					
21	11/13/46	77	12/26/23	67521	California Wil					
22	12/10/65	58	12/22/23	12193	Disaster Reli					
23	11/23/46	77	12/26/23	28635	Disaster Relief	M	M	Married	Caucasian	50
24	11/01/40	83	12/26/23	19426	Disaster Relief	M	M	Married	Caucasian	30
25	02/14/57	66	12/22/23	48412	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Logic for transforming date to age

When month of birth date > month of current date
Then year of current date – (birth year – 1)

When month of birth date = month of current date
And day of birth date > day of current date
Then year of current date – (birth year – 1)

Else year of current date – birth year

As Derived Age

SQL for transforming date to age

```
CASE
WHEN extract(month from birth_dt) > extract(month from current_date) THEN extract(year from current_date) - extract(year from birth_dt) – 1

WHEN extract(month from birth_dt) = extract(month from current_date) AND extract(day from birth_dt) > extract(day from current_date) THEN extract(year from current_date) - extract(year from birth_dt) – 1

ELSE extract(year from current_date) - extract(year from birth_dt)

END AS 'age',
```

Step 2 – Birthdate is removed from sql after transforming it to age

Age	Donation Date	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
71	12/28/23	54220	California Wildfires	M	M	Married	Caucasian	50
72	12/29/23	70001	California Wildfires	M				
81	12/27/23	18444	California Wildfires	M				
59	12/24/23	01460	International	F				
79	12/27/23	37013	Disaster Relief	M				
83	12/29/23	49046	Disaster Relief	M				
86	12/21/23	95404	Disaster Relief	U				
79	12/27/23	29418	Disaster Relief	F				
66	12/29/23	44606	California Wildfires	M				
80	12/26/23	37209	Disaster Relief	F				
36	12/26/23	14526	California Wildfires	U				
78	12/29/23	49442	Disaster Relief	F				
88	12/22/23	59901	Disaster Relief	M				
61	12/27/23	06483	Disaster Relief	M				
61	12/22/23	68506	Disaster Relief	F				
76	12/29/23	43213	Disaster Relief	M				
70	12/26/23	44233	Disaster Relief	M				
75	12/22/23	44149	Disaster Relief	F				
85	12/26/23	08505	California Wildfires	M				
77	12/26/23	67521	California Wildfires	F				
58	12/22/23	12193	Disaster Relief	M				
77	12/26/23	28635	Disaster Relief	M	M	Married	Caucasian	50
83	12/26/23	19426	Disaster Relief	M	M	Married	Caucasian	30
66	12/22/23	48412	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Logic for transforming date to age

When month of birth date > month of current date
Then year of current date – (birth year – 1)

When month of birth date = month of current date
And day of birth date > day of current date
Then year of current date – (birth year – 1)

Else year of current date – birth year

As Derived Age

SQL for transforming date to age

```
CASE
WHEN extract(month from birth_dt) > extract(month from current_date) THEN extract(year from current_date) - extract(year from birth_dt) – 1

WHEN extract(month from birth_dt) = extract(month from current_date) AND extract(day from birth_dt) > extract(day from current_date) THEN extract(year from current_date) - extract(year from birth_dt) – 1

ELSE extract(year from current_date) - extract(year from birth_dt)

END AS 'age',
```

Step 3 – Age or Date of Birth can be transformed to age band

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Age	Age Band	Donation Date	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount					
2	71	65-74	12/28/23	54220	California Wildfires	M	M	Married	Caucasian	50					
3	72	65-74	12/29/23	70001	California Wildfires	M	M	Married	Caucasian	100					
4	81	75-99	12/27/23	18444	California Wildfires	M	M	Married	Caucasian	0					
5	59	55-64	12/24/23	01460	International	F	M	Married	Caucasian	0					
6	79	75-99	12/27/23	37013	Disaster Relief	M	M	Married	Caucasian	100					
7	83	75-99	12/29/23	49046	Disaster Relief	M	M	Married	Caucasian	19					
8	86	75-99	12/21/23	95404	Disaster Relief	U	M	Married	Caucasian	19					
9	79	75-99	12/27/23	29418	Disaster Relief	F	M	Married	Black or African-American	100					
10	66	65-74	12/29/23	44606	California Wildfires	M	M	Married	Caucasian	40					
11	80	75-99	12/26/23	37209	Disaster Relief	F	M	Married	Caucasian	20					
12	36	35-44	12/26/23	14526	California Wildfires	U	M	Married	Asian	25					
13	78	75-99	12/29/23	49442	Disaster Relief	F	S	Single	Black or African-American	20					
14	88	75-99	12/22/23	59901	Disaster Relief	M	M	Married	Black or African-American	57					
15	61	55-64	12/27/23	06483	Disaster Relief	M	M	Married	Asian	15					
16	61	55-64	12/22/23	68506	Disaster Relief	F	M	Married	Caucasian	25					
17	76	75-99	12/29/23	43213	Disaster Relief	M	M	Married	Caucasian	40					
18	70	65-74	12/26/23	44233	Disaster Relief	M	M	Married	Caucasian	100					
19	75	75-99	12/22/23	44149	Disaster Relief	F	S	Single	Caucasian	38					
20	85	75-99	12/26/23	08505	California Wildfires	M	M	Married	Caucasian	50					
21	77	75-99	12/26/23	67521	California Wildfires	F	M	Married	Asian	150					
22	58	55-64	12/22/23	12193	Disaster Relief	M	M	Married	Caucasian	25					
23	77	75-99	12/26/23	28635	Disaster Relief	M	M	Married	Caucasian	50					
24	83	75-99	12/26/23	19426	Disaster Relief	M	M	Married	Caucasian	30					
25	66	65-74	12/22/23	48412	Disaster Relief	F	M	Married	Caucasian	25					

Query 1

Step 3 – Date of Birth can be transformed to age band

Original Age sql statement nested within WITH clause

The WITH Claude in SQL	SQL for transforming date to age
The WITH clause can help you write readable SQL queries and break complex calculations into logical steps. It was added to SQL to simplify complicated long queries. A WITH Clause allows you to create a select statement that returns a temporary result; you can name this result and reference it in another query. Basically, it's a named subquery, but it can be recursive.	WITH AGE Table as (CASE WHEN extract(month from birth_dt) > extract(month from current_date) THEN extract(year from current_date) - extract(year from birth_dt) – 1 WHEN extract(month from birth_dt) = extract(month from current_date) AND extract(day from birth_dt) > extract(day from current_date) THEN extract(year from current_date) - extract(year from birth_dt) – 1 ELSE extract(year from current_date) - extract(year from birth_dt) END AS 'age' from <table1> select Case when age1 <=18 then '18 or less' when age1 >18 and age1<= 25 then '19-25' when age1 >25 and age1<= 50 then '26-50' when age1 >50 and age1<= 65 then '51-65' when age1 >65 then 'Greater than 65' else 'Unknown' end AS Age_Band from <table1>,<table2>

Step 4 – Age column can be removed from sql

	A	B	C	D	E	F	G	H	I
1	Age Band	Donation Date	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
2	65-74	12/28/23	54220	California Wildfires	M	M	Married	Caucasian	50
3	65-74	12/29/23	70001	California Wildfires	M	M	Married	Caucasian	100
4	75-99	12/27/23	18444	California Wildfires	M	M	Married	Caucasian	0
5	55-64	12/24/23	01460	International	F	M	Married	Caucasian	0
6	75-99	12/27/23	37013	Disaster Relief	M	M	Married	Caucasian	100
7	75-99	12/29/23	49046	Disaster Relief	M	M	Married	Caucasian	19
8	75-99	12/21/23	95404	Disaster Relief	U	M	Married	Caucasian	19
9	75-99	12/27/23	29418	Disaster Relief	F	M	Married	Black or African-American	100
10	65-74	12/29/23	44606	California Wildfires	M	M	Married	Caucasian	40
11	75-99	12/26/23	37209	Disaster Relief	F	M	Married	Caucasian	20
12	35-44	12/26/23	14526	California Wildfires	U	M	Married	Asian	25
13	75-99	12/29/23	49442	Disaster Relief	F	S	Single	Black or African-American	20
14	75-99	12/22/23	59901	Disaster Relief	M	M	Married	Black or African-American	57
15	55-64	12/27/23	06483	Disaster Relief	M	M	Married	Asian	15
16	55-64	12/22/23	68506	Disaster Relief	F	M	Married	Caucasian	25
17	75-99	12/29/23	43213	Disaster Relief	M	M	Married	Caucasian	40
18	65-74	12/26/23	44233	Disaster Relief	M	M	Married	Caucasian	100
19	75-99	12/22/23	44149	Disaster Relief	F	S	Single	Caucasian	38
20	75-99	12/26/23	08505	California Wildfires	M	M	Married	Caucasian	50
21	75-99	12/26/23	67521	California Wildfires	F	M	Married	Asian	150
22	55-64	12/22/23	12193	Disaster Relief	M	M	Married	Caucasian	25
23	75-99	12/26/23	28635	Disaster Relief	M	M	Married	Caucasian	50
24	75-99	12/26/23	19426	Disaster Relief	M	M	Married	Caucasian	30
25	65-74	12/22/23	48412	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Step 5 – Donation date can be transformed to first day of month

	A	B	C	D	E	F	G	H	I
1	Age Band	Donation Date	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
2	65-74	12/28/23	54220	California Wildfires	M	M	Married	Caucasian	50
3	65-74	12/29/23	70001	California Wildfires	M	M	Married	Caucasian	100
4	75-99	12/27/23	18444	California Wildfires	M	M	Married	Caucasian	0
5	55-64	12/24/23	01460	International	F	M	Married	Caucasian	0
6	75-99	12/27/23	37013	Disaster Relief	M	M	Married	Caucasian	100
7	75-99	12/29/23	49046	Disaster Relief	M	M	Married	Caucasian	19
8	75-99	12/21/23	95404	Disaster Relief	U	M	Married	Caucasian	19
9	75-99	12/27/23	29418	Disaster Relief	F	M	Married	Black or African-American	100
10	65-74	12/29/23	44606	California Wildfires	M	M	Married	Caucasian	40
11	75-99	12/26/23	37209	Disaster Relief	F	M	Married	Caucasian	20
12	35-44	12/26/23	14526	California Wildfires	U	M	Married	Asian	25
13	75-99	12/29/23	49442	Disaster Relief	F	S	Single	Black or African-American	20
14	75-99	12/22/23	59901	Disaster Relief	M	M	Married	Black or African-American	57
15	55-64	12/27/23	06483	Disaster Relief	M	M	Married	Asian	15
16	55-64	12/22/23	68506	Disaster Relief	F	M	Married	Caucasian	25
17	75-99	12/29/23	43213	Disaster Relief	M	M	Married	Caucasian	40
18	65-74	12/26/23	44233	Disaster Relief	M	M	Married	Caucasian	100
19	75-99	12/22/23	44149	Disaster Relief	F	S	Single	Caucasian	38
20	75-99	12/26/23	08505	California Wildfires	M	M	Married	Caucasian	50
21	75-99	12/26/23	67521	California Wildfires	F	M	Married	Asian	150
22	55-64	12/22/23	12193	Disaster Relief	M	M	Married	Caucasian	25
23	75-99	12/26/23	28635	Disaster Relief	M	M	Married	Caucasian	50
24	75-99	12/26/23	19426	Disaster Relief	M	M	Married	Caucasian	30
25	65-74	12/22/23	48412	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Step 5 – Donation date can be transformed to first day of month

	A	B	C	D	E	F	G	H	I	J
1	Age Band	Donation Date	First Day of Month	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
2	65-74	12/28/23	12/01/23	54220	California Wildfires	M	M	Married	Caucasian	50
3	65-74	12/29/23	12/01/23	70001	California Wildfires	M	M	Married	Caucasian	100
4	75-99	12/27/23	12/01/23	18444	California Wildfires	M	M	Married	Caucasian	0
5	55-64	12/24/23	12/01/23	01460	International	F	M	Married	Caucasian	0
6	75-99	12/27/23	12/01/23	37013	Disaster Relief	M	M	Married	Caucasian	100
7	75-99	12/29/23	12/01/23	49046	Disaster Relief	M	M	Married	Caucasian	19
8	75-99	12/21/23	12/01/23	95404	Disaster Relief	U	M	Married	Caucasian	19
9	75-99	12/27/23	12/01/23	29418	Disaster Relief	F	M	Married	Black or African-American	100
10	65-74	12/29/23	12/01/23	44606	California Wildfires	M	M	Married	Caucasian	40
11	75-99	12/26/23	12/01/23	37209	Disaster Relief	F	M	Married	Caucasian	20
12	35-44	12/26/23	12/01/23	14526	California Wildfires	U	M	Married	Asian	25
13	75-99	12/29/23	12/01/23	49442	Disaster Relief	F	S	Single	Black or African-American	20
14	75-99	12/22/23	12/01/23	59901	Disaster Relief	M	M	Married	Black or African-American	57
15	55-64	12/27/23	12/01/23	06483	Disaster Relief	M	M	Married	Asian	15
16	55-64	12/22/23	12/01/23	68506	Disaster Relief	F	M	Married	Caucasian	25
17	75-99	12/29/23	12/01/23	43213	Disaster Relief	M	M	Married	Caucasian	40
18	65-74	12/26/23	12/01/23	44233	Disaster Relief	M	M	Married	Caucasian	100
19	75-99	12/22/23	12/01/23	44149	Disaster Relief	F	S	Single	Caucasian	38
20	75-99	12/26/23	12/01/23	08505	California Wildfires	M	M	Married	Caucasian	50
21	75-99	12/26/23	12/01/23	67521	California Wildfires	F	M	Married	Asian	150
22	55-64	12/22/23	12/01/23	12193	Disaster Relief	M	M	Married	Caucasian	25
23	75-99	12/26/23	12/01/23	28635	Disaster Relief	M	M	Married	Caucasian	50
24	75-99	12/26/23	12/01/23	19426	Disaster Relief	M	M	Married	Caucasian	30
25	65-74	12/22/23	12/01/23	48412	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Step 5 – Date column can be removed from sql

	A	B	C	D	E	F	G	H	I
1	Age Band	First Day of Month	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
2	65-74	12/01/23	54220	California Wildfires	M	M	Married	Caucasian	50
3	65-74	12/01/23	70001	California Wildfires	M	M	Married	Caucasian	100
4	75-99	12/01/23	18444	California Wildfires	M	M	Married	Caucasian	0
5	55-64	12/01/23	01460	International	F	M	Married	Caucasian	0
6	75-99	12/01/23	37013	Disaster Relief	M	M	Married	Caucasian	100
7	75-99	12/01/23	49046	Disaster Relief	M	M	Married	Caucasian	19
8	75-99	12/01/23	95404	Disaster Relief	U	M	Married	Caucasian	19
9	75-99	12/01/23	29418	Disaster Relief	F	M	Married	Black or African-American	100
10	65-74	12/01/23	44606	California Wildfires	M	M	Married	Caucasian	40
11	75-99	12/01/23	37209	Disaster Relief	F	M	Married	Caucasian	20
12	35-44	12/01/23	14526	California Wildfires	U	M	Married	Asian	25
13	75-99	12/01/23	49442	Disaster Relief	F	S	Single	Black or African-American	20
14	75-99	12/01/23	59901	Disaster Relief	M	M	Married	Black or African-American	57
15	55-64	12/01/23	06483	Disaster Relief	M	M	Married	Asian	15
16	55-64	12/01/23	68506	Disaster Relief	F	M	Married	Caucasian	25
17	75-99	12/01/23	43213	Disaster Relief	M	M	Married	Caucasian	40
18	65-74	12/01/23	44233	Disaster Relief	M	M	Married	Caucasian	100
19	75-99	12/01/23	44149	Disaster Relief	F	S	Single	Caucasian	38
20	75-99	12/01/23	08505	California Wildfires	M	M	Married	Caucasian	50
21	75-99	12/01/23	67521	California Wildfires	F	M	Married	Asian	150
22	55-64	12/01/23	12193	Disaster Relief	M	M	Married	Caucasian	25
23	75-99	12/01/23	28635	Disaster Relief	M	M	Married	Caucasian	50
24	75-99	12/01/23	19426	Disaster Relief	M	M	Married	Caucasian	30
25	65-74	12/01/23	48412	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Step 6 – Replace Zip 5 with Region

	A	B	C	D	E	F	G	H	I	J
1	Age Band	First Day of Month	Zip 5	Region	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
2	65-74	12/01/23	54220	East Region	California Wildfires	M	M	Married	Caucasian	50
3	65-74	12/01/23	70001	Midwest Region	California Wildfires	M	M	Married	Caucasian	100
4	75-99	12/01/23	18444	Midwest Region	California Wildfires	M	M	Married	Caucasian	0
5	55-64	12/01/23	01460	South Region	International	F	M	Married	Caucasian	0
6	75-99	12/01/23	37013	East Region	Disaster Relief	M	M	Married	Caucasian	100
7	75-99	12/01/23	49046	Midwest Region	Disaster Relief	M	M	Married	Caucasian	19
8	75-99	12/01/23	95404	West Region	Disaster Relief	U	M	Married	Caucasian	19
9	75-99	12/01/23	29418	East Region	Disaster Relief	F	M	Married	Black or African-American	100
10	65-74	12/01/23	44606	East Region	California Wildfires	M	M	Married	Caucasian	40
11	75-99	12/01/23	37209	West Region	Disaster Relief	F	M	Married	Caucasian	20
12	35-44	12/01/23	14526	Midwest Region	California Wildfires	U	M	Married	Asian	25
13	75-99	12/01/23	49442	East Region	Disaster Relief	F	S	Single	Black or African-American	20
14	75-99	12/01/23	59901	East Region	Disaster Relief	M	M	Married	Black or African-American	57
15	55-64	12/01/23	06483	South Region	Disaster Relief	M	M	Married	Asian	15
16	55-64	12/01/23	68506	Midwest Region	Disaster Relief	F	M	Married	Caucasian	25
17	75-99	12/01/23	43213	West Region	Disaster Relief	M	M	Married	Caucasian	40
18	65-74	12/01/23	44233	West Region	Disaster Relief	M	M	Married	Caucasian	100
19	75-99	12/01/23	44149	East Region	Disaster Relief	F	S	Single	Caucasian	38
20	75-99	12/01/23	08505	West Region	California Wildfires	M	M	Married	Caucasian	50
21	75-99	12/01/23	67521	Midwest Region	California Wildfires	F	M	Married	Asian	150
22	55-64	12/01/23	12193	West Region	Disaster Relief	M	M	Married	Caucasian	25
23	75-99	12/01/23	28635	East Region	Disaster Relief	M	M	Married	Caucasian	50
24	75-99	12/01/23	19426	West Region	Disaster Relief	M	M	Married	Caucasian	30
25	65-74	12/01/23	48412	South Region	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Step 6 – Replace Zip 5 with Region using Simplemaps or Organization's Data

simplemaps.com/data/us-zips

simplemaps
Interactive Maps & Data

US Cities Zips Counties Neighborhoods World Cities Pricing All

US Zip Codes Database

We're proud to offer a simple, accurate and up-to-date database of US Zip Codes. It's been built from the ground up using authoritative sources including the U.S. Postal Service™, U.S. Census Bureau, National Weather Service, American Community Survey, and the IRS.

- **Up-to-date:** Data updated as of October 30, 2023. Includes data from 2020 Census and 2021 ACS!
- **Comprehensive**: 41,690 unique zip codes including ZCTA, unique, military, and PO box zips.
- **Useful fields**: From latitude and longitude to household income.
- **Accurate**: Aggregated from official sources and precisely geocoded to latitude and longitude.
- **Simple:** A single CSV file, concise field names, only one entry per zip code.

Databases

	Basic	Pro	Comprehensive
Commercial use	Allowed	Allowed	Allowed
File format	CSV, Excel	CSV, Excel, SQL	CSV, Excel, SQL
Census-designated zips	Yes, all ZCTAS	Yes, all ZCTAS	Yes, all ZCTAS
Current USPS zips	Most	Yes, all USPS zips	Yes, all USPS zips
Number of entries	33,788	41,690	41,690
Fields (listed below)	Basic fields	More fields	All fields
Future updates	Not guaranteed	Included for 12 months	Included for 24 months
Attribution	Required	Not required	Not required
License	Creative Commons Attribution 4.0	Permissive, no redistribution	Permissive, no redistribution
Refund policy	N/A	30-day guarantee	30-day guarantee
One-time fee	Free	$99	$199
	Download	Buy Now!	Buy Now!

Customer Approved

Step 7 – Zip 5 can be removed from sql – Final Aggregate Dataset

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Age Band	First Day of Month	Region	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount					
2	65-74	12/01/23	East Region	California Wildfires	M	M	Married	Caucasian	50					
3	65-74	12/01/23	Midwest Region	California Wildfires	M	M	Married	Caucasian	100					
4	75-99	12/01/23	Midwest Region	California Wildfires	M	M	Married	Caucasian	0					
5	55-64	12/01/23	South Region	International	F	M	Married	Caucasian	0					
6	75-99	12/01/23	East Region	Disaster Relief	M	M	Married	Caucasian	100					
7	75-99	12/01/23	Midwest Region	Disaster Relief	M	M	Married	Caucasian	19					
8	75-99	12/01/23	West Region	Disaster Relief	U	M	Married	Caucasian	19					
9	75-99	12/01/23	East Region	Disaster Relief	F	M	Married	Black or African-American	100					
10	65-74	12/01/23	East Region	California Wildfires	M	M	Married	Caucasian	40					
11	75-99	12/01/23	West Region	Disaster Relief	F	M	Married	Caucasian	20					
12	35-44	12/01/23	Midwest Region	California Wildfires	U	M	Married	Asian	25					
13	75-99	12/01/23	East Region	Disaster Relief	F	S	Single	Black or African-American	20					
14	75-99	12/01/23	East Region	Disaster Relief	M	M	Married	Black or African-American	57					
15	55-64	12/01/23	South Region	Disaster Relief	M	M	Married	Asian	15					
16	55-64	12/01/23	Midwest Region	Disaster Relief	F	M	Married	Caucasian	25					
17	75-99	12/01/23	West Region	Disaster Relief	M	M	Married	Caucasian	40					
18	65-74	12/01/23	West Region	Disaster Relief	M	M	Married	Caucasian	100					
19	75-99	12/01/23	East Region	Disaster Relief	F	S	Single	Caucasian	38					
20	75-99	12/01/23	West Region	California Wildfires	M	M	Married	Caucasian	50					
21	75-99	12/01/23	Midwest Region	California Wildfires	F	M	Married	Asian	150					
22	55-64	12/01/23	West Region	Disaster Relief	M	M	Married	Caucasian	25					
23	75-99	12/01/23	East Region	Disaster Relief	M	M	Married	Caucasian	50					
24	75-99	12/01/23	West Region	Disaster Relief	M	M	Married	Caucasian	30					
25	65-74	12/01/23	South Region	Disaster Relief	F	M	Married	Caucasian	25					

Query 1

Two Important SQL Date Functions

	A	B	C	D	E	F	G	H	I
1	Age Band	First Day of Month	Zip 5	Fund Desc	Gender Code	Marital Status Code	Marital Status	Ethnicity	Donation Amount
2	65-74	12/01/23	54220	California Wildfires	M	M	Married	Caucasian	50
3	65-74	12/01/23	70001	California Wildfires	M	M	Married	Caucasian	100
4	75-99	12/01/23	18444	California Wildfires	M	M	Married	Caucasian	0
5	55-64	12/01/23	01460	International	F	M	Married	Caucasian	0
6	75-99	12/01/23	37013	Disaster Relief	M	M	Married	Caucasian	100
7	75-99	12/01/23	49046	Disaster Relief					
8	75-99	12/01/23	95404	Disaster Relief					
9	75-99	12/01/23	29418	Disaster Relief					
10	65-74	12/01/23	44606	California Wildfi					
11	75-99	12/01/23	37209	Disaster Relief					
12	35-44	12/01/23	14526	California Wildfi					
13	75-99	12/01/23	49442	Disaster Relief					
14	75-99	12/01/23	59901	Disaster Relief					
15	55-64	12/01/23	06483	Disaster Relief					
16	55-64	12/01/23	68506	Disaster Relief					
17	75-99	12/01/23	43213	Disaster Relief					
18	65-74	12/01/23	44233	Disaster Relief					
19	75-99	12/01/23	44149	Disaster Relief					
20	75-99	12/01/23	08505	California Wildfi					
21	75-99	12/01/23	67521	California Wildfi					
22	55-64	12/01/23	12193	Disaster Relief					
23	75-99	12/01/23	28635	Disaster Relief					
24	75-99	12/01/23	19426	Disaster Relief					
25	65-74	12/01/23	48412	Disaster Relief	F	M	Married	Caucasian	25

Query 1

Two important date functions	SQL
Transforms Date to first day of the month for the date used in the function. This is important because a SAC timeline chart types look for a date. For that reason, in an aggregate data set it's best to aggregate on the first day of the month.	trunc(order_date,'MM')
Transforms Date to first day of <u>any</u> month counting backwards month by month based on the 2nd second parameter of the add-months function Used in the WHERE Condition of the query	trunc(add_months(order_date,-24),'MM') Where Condition Example: Where ORDER_DATE >= trunc(add_months(order_date,-24),'MM') And ORDER_DATE <= current_date

Room204 5G

Wrap Up

Building a good model is the hardest part of analytical reporting. Using some of the techniques in this presentation will make it easier to do so.

Downloading the presentation will help to remember the methodology of this presentation

Where to Find More Information

SAP Analytics Cloud blog

https://blogs.sap.com/tags/67838200100800006884/

SAP Analytics Cloud Release Highlights

https://www.sap.com/india/products/technology-platform/cloud-analytics/features/release-highlights.html

YouTube Channel for SAP Analytics Cloud training

https://www.youtube.com/playlist?list=PLs5htBIwERYWSixKSqQHzndop33aBCz1U

Key Points to Take Home

- The SAP analytics cloud dataset paradigm is the most affective type of model for operational reporting and is the primary reason why it is the leader in augmented analytics among SaaS analytic tools
- SAP Business Objects is designed to use the Live Query connection most effectively and that is why it is the preferred tool for operational and ad-hoc reporting in most cases
- The concept of dimensionality is important for model building. Merging small datasets that are based on the theme of a story can greatly reduce row count
- The main 3 transformations need to convert a transactional dataset to an aggregate dataset that is suitable for analytical stories are person or organization to an attribute such as person or org type; Zip or address to a less granular value such as region or state; Date of transaction converted to month-year or preferably first day of the month

Thank you! Any Questions?

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Please remember to complete your session evaluation.

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