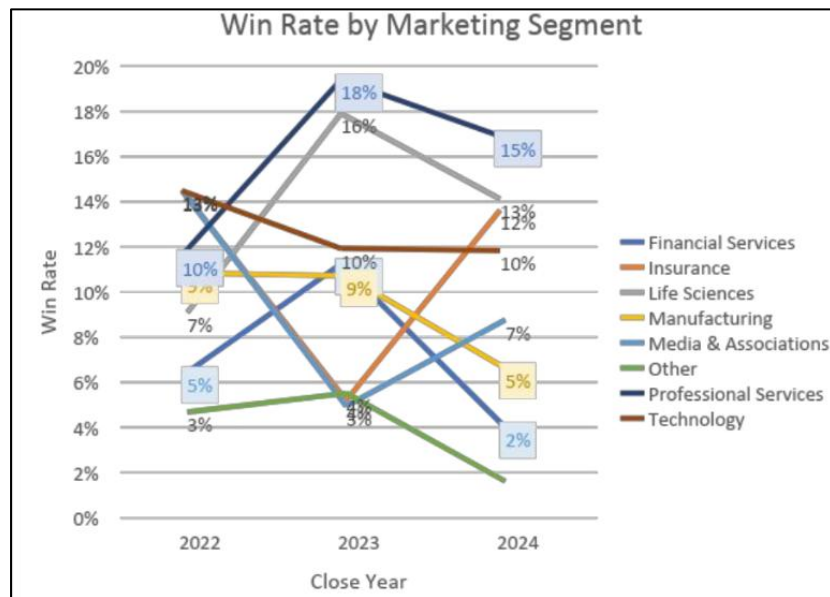
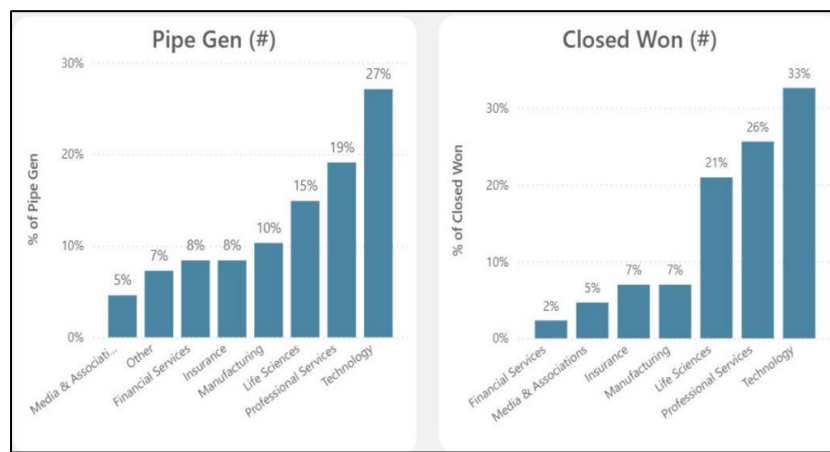
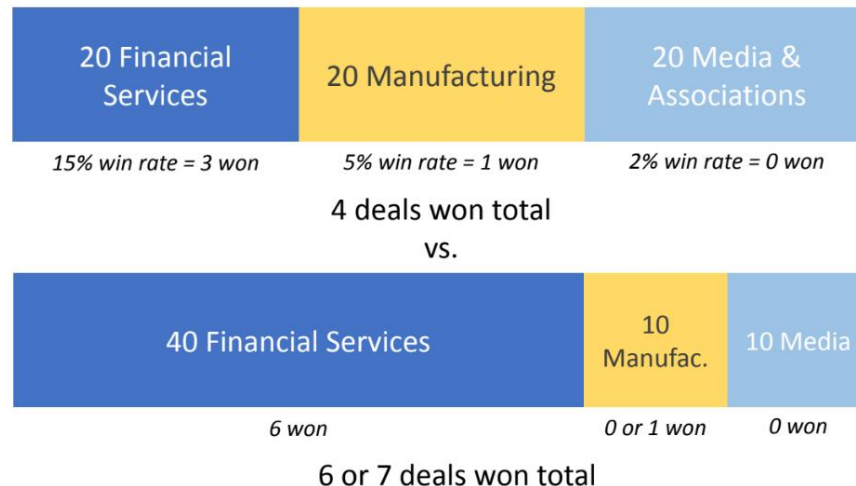


Account Scoring Power BI Dashboard

Motivation for an Account Scoring Model



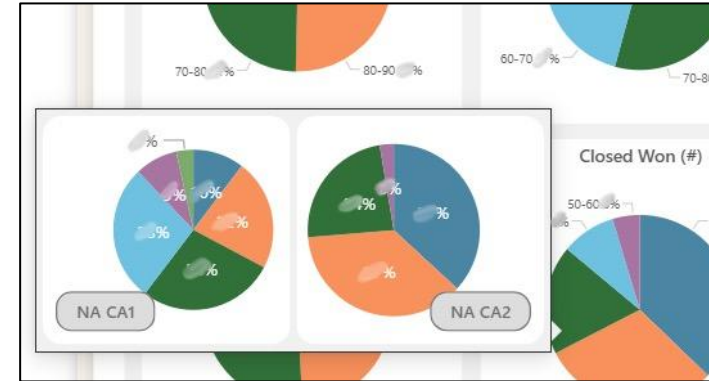
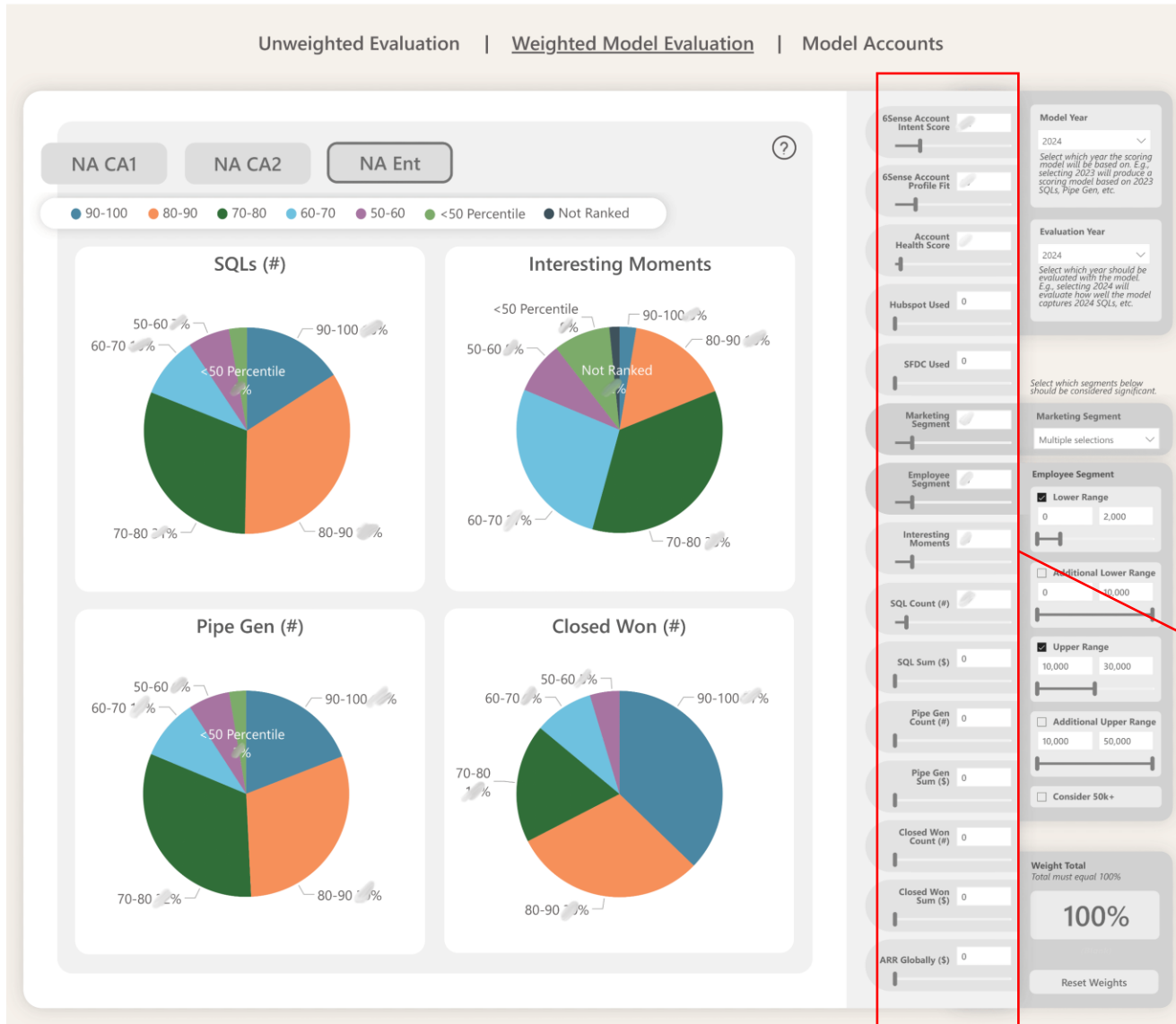
Consider 60 accounts and 2024 win rates.



- Goal is to identify trends between the data we track (i.e., 6Sense data, marketing segment, etc.) and closed won deals. For example, Professional Services clearly has a higher win rate than Manufacturing.
- Accounts with higher probabilities of winning are prioritized over accounts with lower probabilities.
- We want to pursue accounts that we historically have a greater chance of winning. For example, % breakdown of pipe gen and closed won by marketing segment shows us that certain industries make up a greater % of pipe gen and closed won vs other industries.

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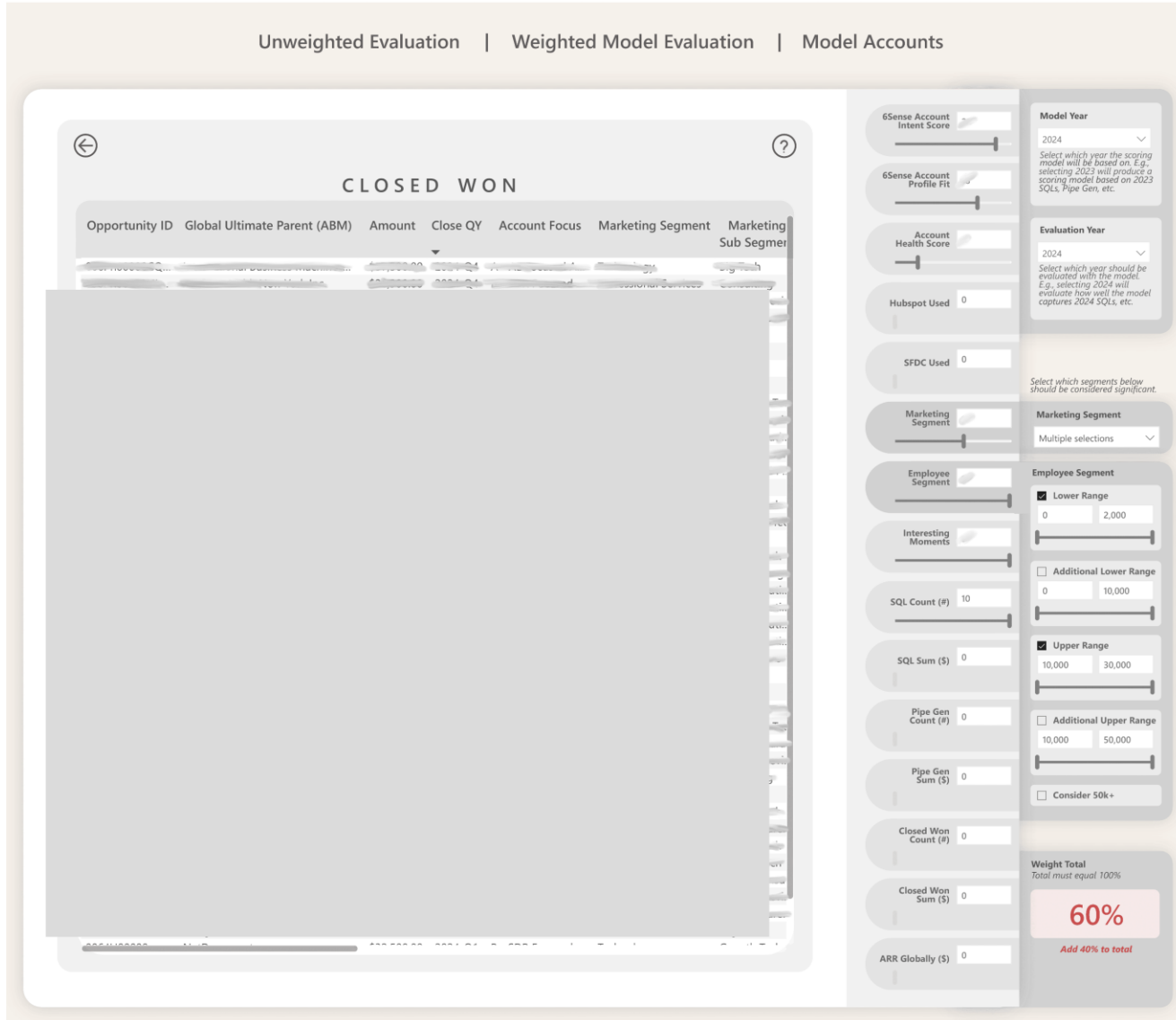
Weighted Model Evaluation



- Accounts are divided into Percentile ranges for ranking purposes. Accounts scored in the 90th - 100th percentile are considered the 'best' accounts by our model. These accounts should be prioritized by the team as they most closely align with future opportunity activity.
- The model ranks accounts according to weights assigned to each category (user-adjustable via sliders on the right of the dashboard)
- The weights are collaborative and completely adjustable, which allows us to prioritize trends across various industries or other forward-looking themes.

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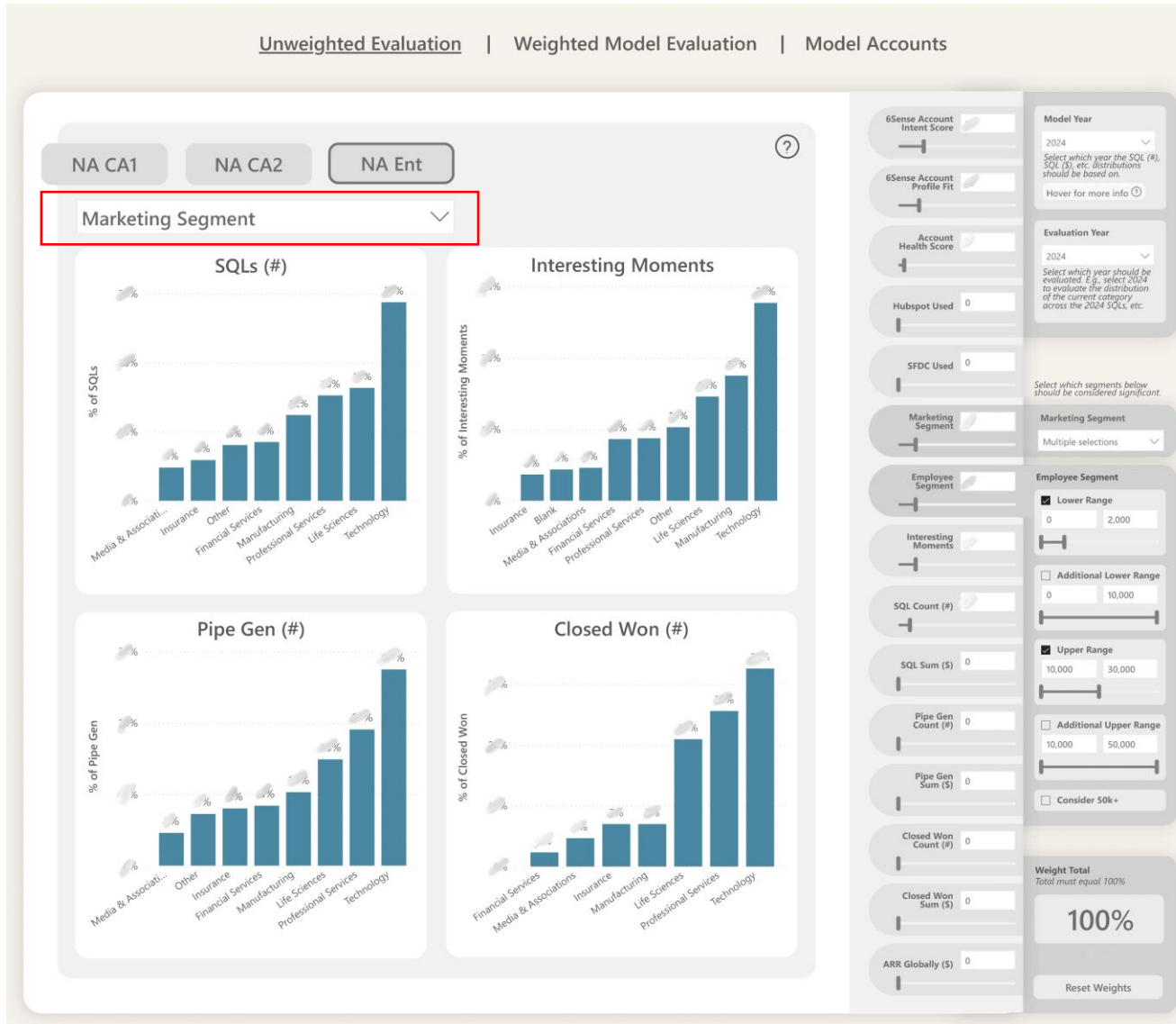
Drill Through Table



- Because the graphs in the previous slide represent the % breakdown of each score percentile across SQLs, Closed Won, etc., we can drill through each graph and see the underlying Salesforce data driving each evaluation.
- This is an example of the table we see when we drill through the 'Closed Won' graph.

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Unweighted Evaluation



- To better inform how weights are determined, navigate to the 'Unweighted Evaluation' tab.
- All factors are available here in the dropdown. We can see the distribution of a factor across SQLs, Pipe Gen, etc.
- In this example we can see Tech is the primary segment for SQLs, thereby suggesting we should lean into tech accounts more possibly and thus increase its weight via the slider.

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Model Accounts & DAX

Unweighted Evaluation | Weighted Model Evaluation | Model Accounts

NA CA1 | NA CA2 | **NA Ent**

Global Ultimate Parent (ABM)	Value Score	Value Bucket	Account Focus	Marketing Segment	Marketing Sub Segment	Employee Segment	Health Score
...

6Sense Account Intent Score

6Sense Account Profile Fit

Account Health Score

Hubspot Used

SFDC Used

Marketing Segment

Employee Segment

Interesting Moments

SQL Count (#)

SQL Sum (\$)

Pipe Gen Count (#)

Pipe Gen Sum (\$)

Closed Won Count (#)

Closed Won Sum (\$)

ARR Globally (\$)

Weight Total
Total must equal 100%

100%

Reset Weights

```
84 ////////////////////////////////////////////////// FINAL VALUE SCORE ////////////////////////////////////////
85
86 -- calculate value score by multiplying each score to their weights
87 VAR value_score =
88     (score_accIntScore * (MAX('_weight_6sense account intent score'[Value]))/100) +
89     (score_accProfileFit * (MAX('_weight_6sense account profile fit'[Value]))/100) +
90     (score_accHealth * (MAX('_weight_account health score'[Value]))/100) +
91     (score_empSeg * (MAX('_weight_employee segment'[Value]))/100) +
92     (score_hubspot * (MAX('_weight_hubspot used'[Value]))/100) +
93     (score_sfdc * (MAX('_weight_sfdc used'[Value]))/100) +
94     (score_marSeg * (MAX('_weight_marketing segment'[Value]))/100) +
95     (score_intMom * (MAX('_weight_interesting moments'[Value]))/100) +
96     (score_sqlCount * (MAX('_weight_sqls #'[Value]))/100) +
97     (score_sqlSum * (MAX('_weight_sqls $'[Value]))/100) +
98     (score_pipeCount * (MAX('_weight_pipe gen #'[Value]))/100) +
99     (score_pipeSum * (MAX('_weight_pipe gen $'[Value]))/100) +
100    (score_wonCount * (MAX('_weight_closed won #'[Value]))/100) +
101    (score_wonSum * (MAX('_weight_closed won $'[Value]))/100) +
102    (score_arrSum * (MAX('_weight_arr globally'[Value]))/100)
103
104 return IF(ISBLANK(SELECTEDVALUE('na ca1_model'[Global Ultimate Parent (ABM)])), "Blank", value_score)
```

Glimpse of DAX code behind calculating value scores.

- Once we're comfortable with the weights, navigate to the 'Model Accounts' tab, which lists all accounts and their respective score based on the weights assigned.
- We can easily export this data for the team to review in excel/csv.

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*How were accounts scored
prior to this dashboard?*

Obtain Weights for Model via Logistic Regression in R

```
46
47 # perform logistic regression
48 full_model <- glm(pipe_gen ~ ., data=dataset, family=binomial)
49 model_probs <- full_model %>% predict(dataset, type="response")
50 process_probs <- preProcess(as.data.frame(model_probs), method=c("range"))
51 norm_probs <- predict(process_probs, as.data.frame(model_probs))
52 summary1[[i]] = summary(full_model)
53 }
54
55 # RESULTS
56 coeffs <- (full_model$coefficients)[-1]
57 process <- preProcess(as.data.frame(coeffs), method=c("range"))
58 norm_coeffs <- predict(process, as.data.frame(coeffs))
59 weights <- (norm_coeffs/sum(norm_coeffs))*100
60 weights <- format(round(weights,2), nsmall=2)
61 df <- data.frame(coeffs, norm_coeffs, weights)
62 df <- df %>% rename("original coeffs"=coeffs,
63                   "normalized"=coeffs.1,
64                   "weights (%)"=coeffs.2)
65 df
```

	Original Coeffs	Normalized		Weights
Account Health Score	0.51640369	0.3738399	0.37/2.21 =	16.94%
6Sense Account Intent Score	0.80258252	0.5972739	0.6/2.21 =	27.06%
6Sense Account Profile Fit	1.31840252	1.0000000	1/2.21 =	45.30%
Global Ultimate Parent Employee Count	0.03758173	0.0000000	0/2.21 =	0.00%
Interesting Moments	0.34022550	0.2362889	0.24/2.21 =	10.70%
Sum		2.2074027		100%

Input Weights into Excel Model & Identify Target Accounts

A	B	C	D	E	F	G	H	I	J	K	
		Marketing Segment		Employee Segment		Health Score	6sense	6sense	#Interesting Moments	Has SQLs ?	
2024	Weight in Scoring	15%		15%		5%	22%	18%	15%	10%	
Ultimate Parent Comp	Account Owner	Segment	Sub Segment	Employee Segment	Focus Rating	Health Score	6sense intent Score	6sense profile score	Interesting Moments This Year	SQLs Created this year	C
Autodesk, Inc.	Peter Finn	Manufacturing	Manufacturer	10K-15K	B - SDR Focused	5	95	Strong	59	\$ 268,900.00	\$
SL LIMITED	Julia Clapper	Life Sciences	Pharmaceuticals	20K-30K	A - AF Focused	5	93	Strong	25	\$ 330,551.28	\$

		Percentile Normalization Ranking							
Value Score	Percentile of Score	Marketing Segment	Employee Segment	Health Score	6sense intent Score	6sense profile score	#Interesting Moments	SQLs	
0.99	100%	1	1	1	0.95	1.00	0.998	0.997	
0.98	100%	1	1	1	0.93	1.00	0.993	0.998	
0.98	100%	1	1	1	0.94	1.00	0.995	0.955	
0.98	100%	1	1	1	0.92	1.00	0.997	0.996	

Weights were further adjusted based on conversations with Sales Managers and regional VPs. Above are screenshots of columns that are weighted and their normalized counterparts. After normalization, each account is assigned a Value Score intended to help identify target accounts.

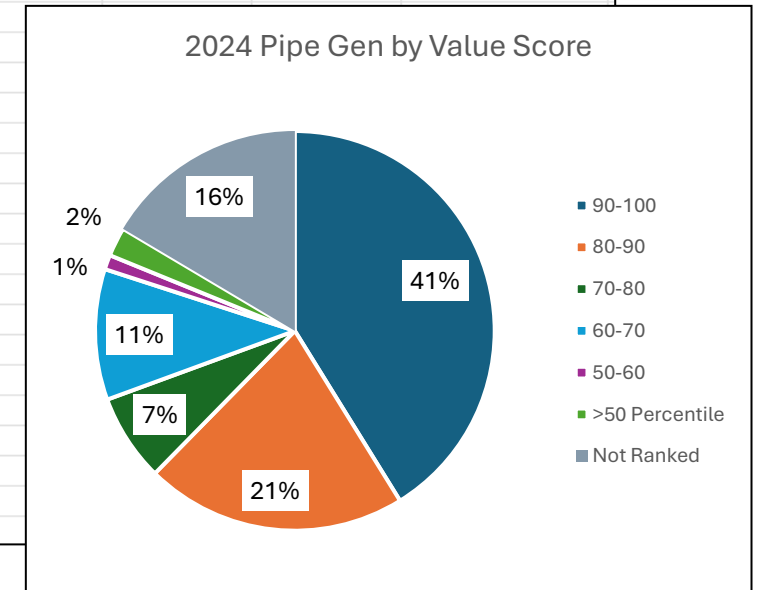
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Check if model is properly capturing accounts

F	G		H	I		J	K	L		M	N	O	P	Q
Value Score	Percentile of Score	2023				2024								
		Interesting Moments	SQLs	Elite Pipe Gen	Closed Won	Interesting Moments	SQLs	SQLs (#)	Elite Pipe Gen	Elite Pipe Gen	Closed Won			
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	
0.1	0%	0	\$ -	\$ -	\$ -	0	\$ -	-	\$ -	-	\$ -	-	\$ -	

2024 Pipe Gen by Value Score

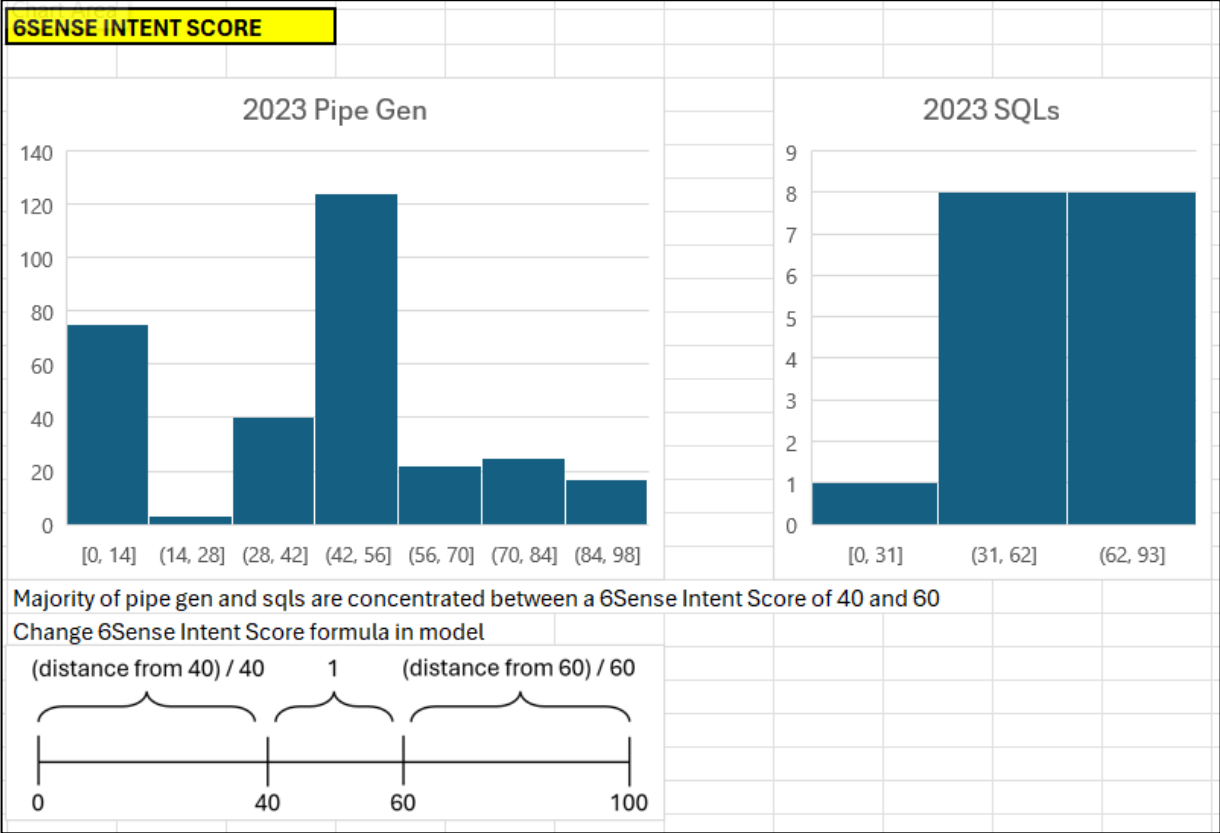
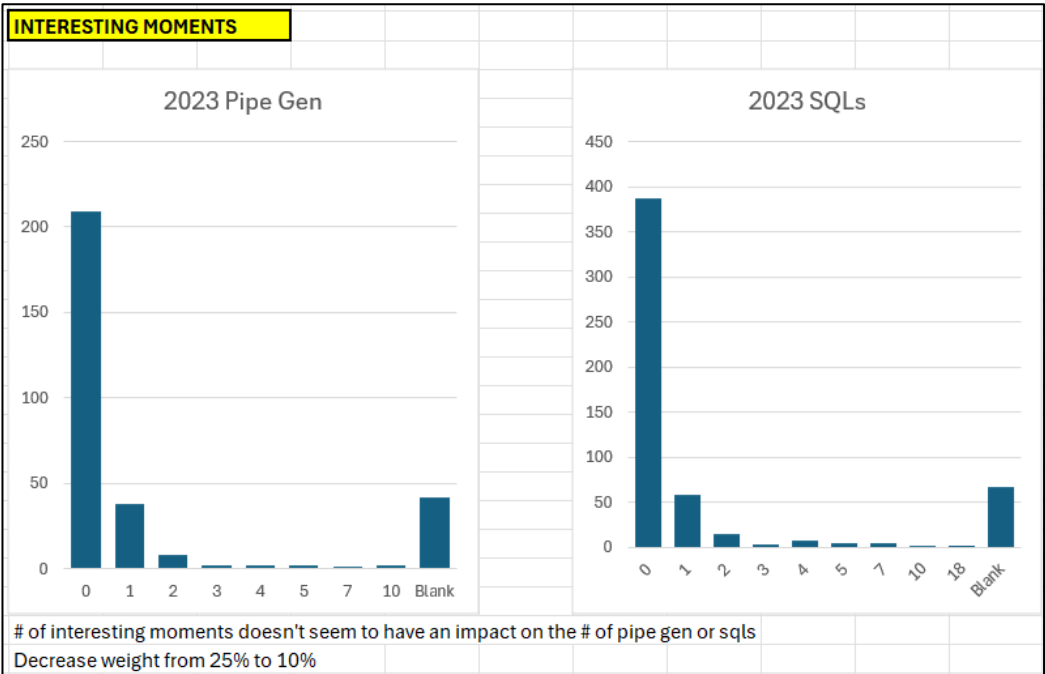
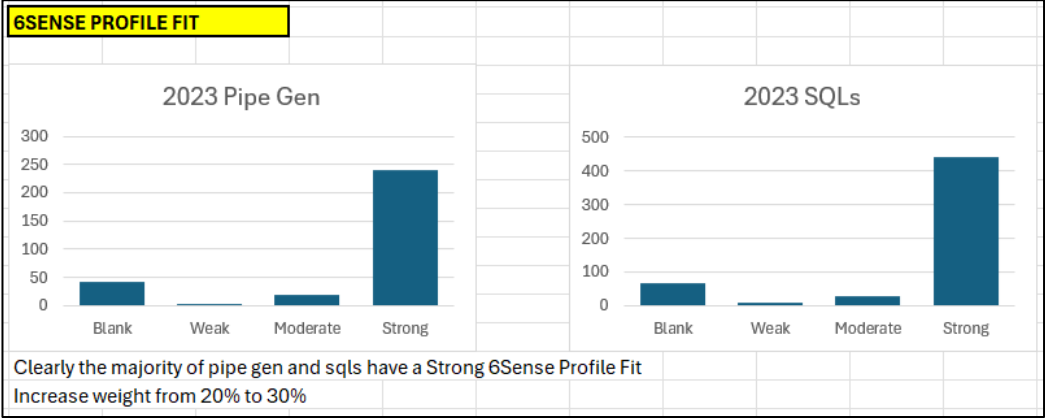
Value Score Range	Percentage
90-100	41%
80-90	21%
70-80	7%
60-70	11%
50-60	2%
>50	1%



Since the model was based on 2023 data, we check 3 months into 2024 to see if the model is properly capturing the intended accounts (i.e., we want to see if the higher value scores are reflected in the pipeline generated). The high percentage makeup of '90-100' scored accounts indicates a good model but will be improved upon based on the current data collected.

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Check if model is properly capturing accounts (cont.)



In the case that the model is inaccurate for a particular team, we look at each factor individually and adjust accordingly.

Check if model is properly capturing accounts (cont.)

