

Customer Experience



Final Presentation

Eva Balogun, Data Analyst Intern for Customer Care

About Me

- Name: Eva Balogun
- Working in Customer Care department under the supervision of Rebecca Hageman
- Mentor: Ryan Gasser
- Rotation Number: 1
- Education: Northeastern University (Boston, MA) studying Data Science & Economics
- Year: Rising Junior



Date, 20XX Meeting

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** Customer Experience

Back Office Volume Analysis

Data Overview



- Data is divided by region
- Combined multiple datasets to create a comprehensive dataset
- The dataset originally had data points for each day, modified to be weekly
- Grouped by type: Low Volume, Reports, Implausible, Meter, & System

Original – daily

	east_outage_minutes	east_low_temp	east_high_temp	east_read_rate	smart_meter_percent_east	volume	original_date
0	123546.5	33.075666	42.790991	0.962059	0.000000	95.0	1/1/17 12:00 AM
1	538088.0	39.448283	44.771167	0.962059	0.000000	1971.0	1/2/17 12:00 AM
2	1089908.5	28.740389	48.590935	0.962059	0.000000	1816.0	1/3/17 12:00 AM
3	224186.5	22.585012	29.225520	0.962059	0.000000	1897.0	1/4/17 12:00 AM
4	668748.5	18.035062	27.684182	0.962059	0.000000	1958.0	1/5/17 12:00 AM
2299	501379.0	40.746878	58.726035	0.935877	0.503646	887.0	4/26/23 12:00 AM
2300	528946.0	44.529193	61.409415	0.935877	0.503646	867.0	4/27/23 12:00 AM
2301	843111.5	49.407569	56.968500	0.935877	0.503646	308.0	4/28/23 12:00 AM
2302	1101579.0	48.961422	56.209695	0.935877	0.503646	559.0	4/29/23 12:00 AM
2303	1523930.5	49.248164	58.628367	0.935877	0.503646	39.0	4/30/23 12:00 AM

Modified - weekly

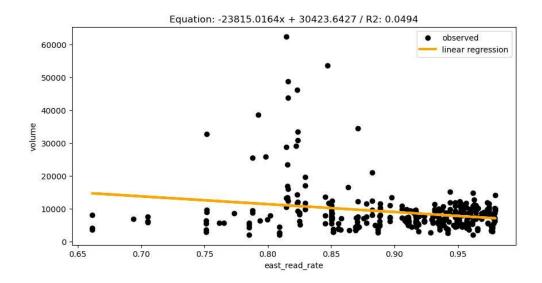
	east_low_temp	east_high_temp	east_read_rate	smart_meter_percent_east	east_outage_minutes	volume
original_date						
2017-01-02	36.261974	43.781079	0.962059	0.000000	661634.5	2066.0
2017-01-09	17.735858	30.995072	0.962059	0.000000	3789873.5	9422.0
2017-01-16	32.391600	46.780232	0.962059	0.000000	5415432.0	14784.0
2017-01-23	37.983389	47.211010	0.962059	0.000000	8219837.5	10769.0
2017-01-30	31.072805	41.641096	0.962059	0.000000	1777461.0	10191.0
2023-04-03	37.104649	56.814792	0.942823	0.501024	148740356.5	5935.0
2023-04-10	41.918592	64.356957	0.935877	0.503646	5212790.5	4765.0
2023-04-17	54.548001	77.421293	0.935877	0.503646	8501547.5	5981.0
2023-04-24	44.999370	64.178418	0.935877	0.503646	10863666.0	4280.0
2023-05-01	45.401151	58.294004	0.935877	0.503646	5155322.5	3547.0

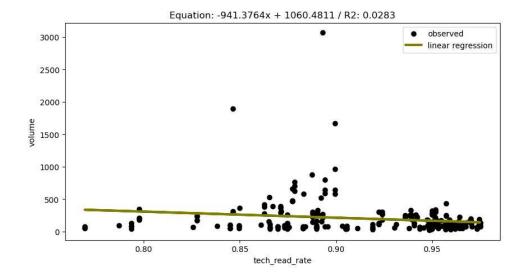




Linear Regressions

- These linear regressions predict volume based on each feature from the dataset
- Each regression includes a coefficient and R2 score
- The R2 scores are low but the overall R2 score was 50%









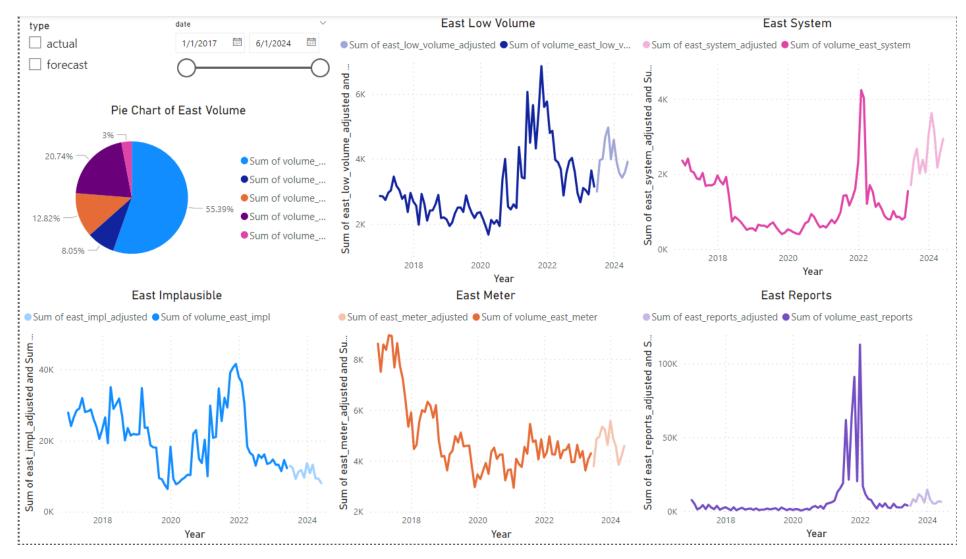
R² Scores by Feature

	Low Temp	High Temp	Read Rate	Smart Meter Percentage	Outage Minutes
East	0	0	4	0	0
Southwest	0	0	6	0	0
Tech	0	1	2	7	0
East Low Volume	0	0	8	13	0
Southwest Low Volume	0	0	0	2	0
Tech Low Volume	0	1	2	8	0
East Reports	0	0	7	4	0
Southwest Reports	0	0	2	4	0
East Implausible	0	0	0	8	1
Southwest Implausible	0	0	7	3	0
East Meter	4	4	13	31	1.5
Southwest Meter	0	0	0	1.6	0
East System	1.5	1	0	2	0
Southwest System	0	0	3	0	0

Change in Volume Based on 1% increase in Feature

	Low Temp	High Temp	Read Rate	Smart Meter Percentage	Outage Minutes
East			-238.15		
Southwest			-289.78		
Tech			-9.41	4.32	
East Low Volume			-12.37	4.41	
Southwest Low Volume				11.45	
Tech Low Volume			-9.41	4.32	
East Reports			-237.4	51.83	
Southwest Reports			-58.84	21.13	
East Implausible				-27.2	
Southwest Implausible			-154.04	-24.5	
East Meter	4.9	4.72	21.21	-9.15	
Southwest Meter					
East System				-1.08	
Southwest System			-3.77		

Dashboard: Region Summary Page



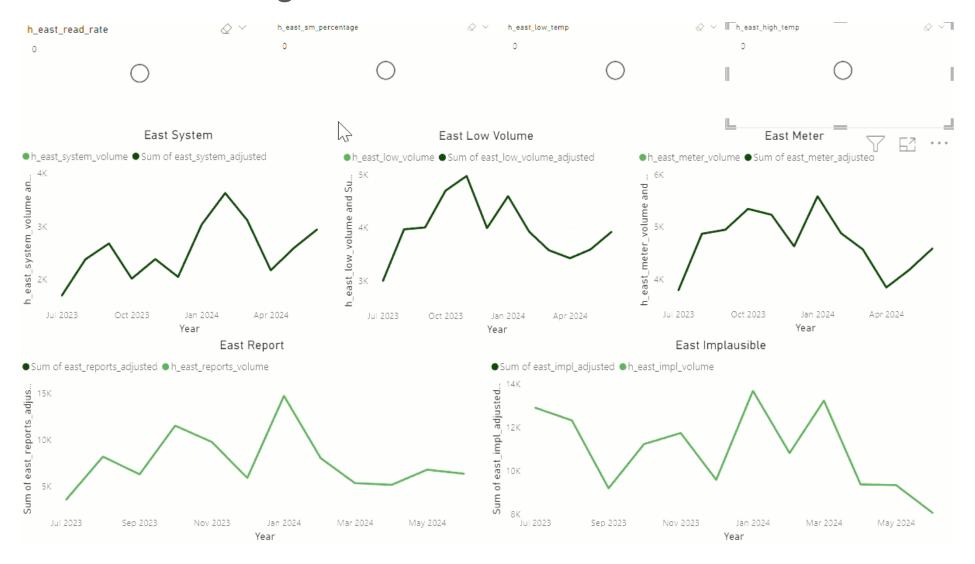




Meeting

Dashboard: Levers Page









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Rev Ops: Segmenting Customers Based on Payment Patterns

Data Overview: Initial Dataset

- Combined multiple datasets (main account, arrears, payment type, etc.) to create a comprehensive dataset for analysis
- Each account appears once, even if they have made multiple payments
- Created a moratorium indicator to signify whether a customer tends to pay within or outside of moratorium
- Segmented customers by payment/arrears data but also included several demographic and general account information

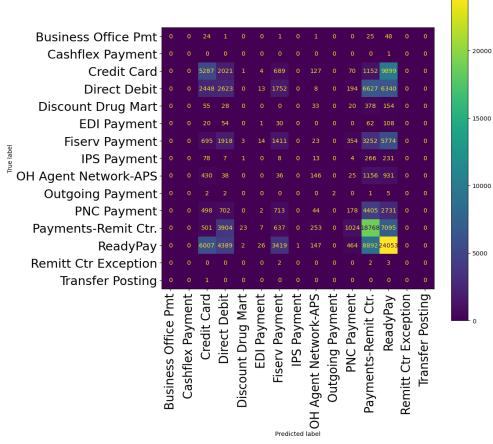
contract_account doc_ty	ype zip_code	email_indicato e	bill_indicator	low_income_indicato	budget_indicator	alert_indicato	customer_age	account_age Total B	Balance 1-30 Total Bal	ance 31-60 Total E	Balance 61-90 Total Bala	nce 91-120 Total Ba	alance >120 sum_	ayment r	moratorium_indicato	propensity_to_rol t	.otal_arrears	payment_cour
1.10162E+11 Ready	Pay 21769	1	1	0	0	0	32	0	0	0	0	0	0	234	1	0	0	
1.10162E+11 Ready	Pay 43537	1	1	0	0	0	30	0	0	0	0	0	0	60	1	0	0	
1.10162E+11 Ready	Pay 43566	1	1	0	0	0	28	0	0	0	0	0	0	66.81	1	0	0	
1.10162E+11 Ready	Pay 26554	1	1	0	0	0	51.5008694	0	0	0	0	0	0	103	1	0	0	
1.10162E+11 Ready	Pay 21703	1	1	0	0	1	29	0	0	0	0	0	0	198	1	0	0	
1.10162E+11 Credit	Car 43614	1	0	1	. 0	0	32	0	0	0	0	0	0	563	1	0	0	
1.10162E+11 Ready	Pay 44136	1	1	0	0	1	26	0	0	0	0	0	0	60	1	0	0	
1.10162E+11 Ready	Pay 26501	1	1	0	0	0	51.5008694	0	0	0	0	0	0	144	1	0	0	
1.10162E+11 Credit	Car 43140	1	0	0	0	0	51.5008694	0	0	0	0	0	0	179	1	0	0	
1.10162E+11 Readyl	Pay 44240	1	1	0	0	1	22	0	0	0	0	0	0	61	1	0	0	
1.10162E+11 Credit	Car 43302	1	1	1	. 0	0	36	0	0	0	0	0	0	134.57	1	0	0	

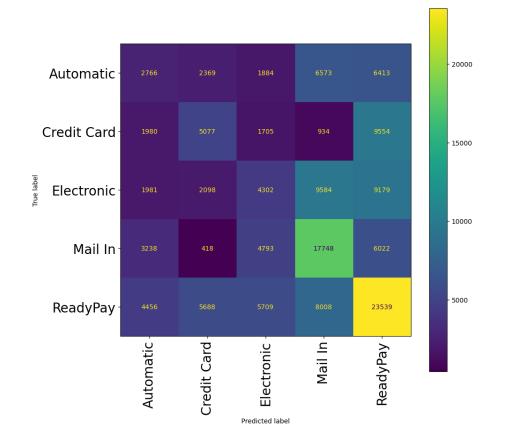




Initial Models

- Created a confusion matrix to predict payment preference based on features in the dataset
- R2 score of 62% when predicting moratorium indicator based on other features







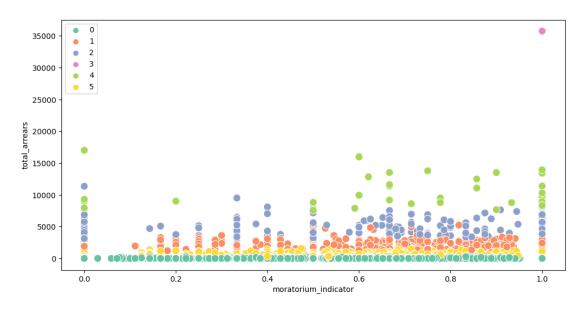


Cluster Model

Original

 Full feature list: arrears (buckets & total), email indicator, e-bill indicator, low-income indicator, budget indicator, alert indicator, customer age, account age, moratorium indicator, propensity to roll

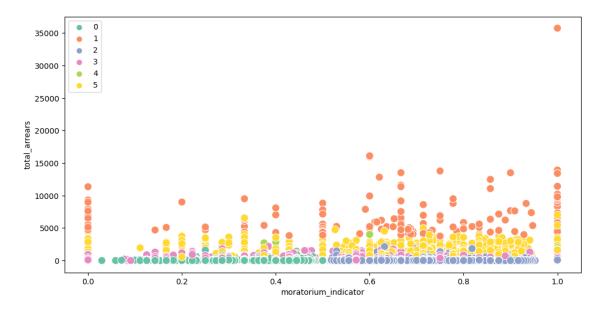
clusters of customers based on payment habits



Normalized

 Full feature list: arrears (buckets & total), alert indicator, moratorium indicator, field visit payment, field visit disconnection, winter dunning starts, summer dunning starts

clusters of customers based on payment habits







Cluster Characteristics

- Group 0: low arrears, rarely starts the dunning process, tends to pay outside of moratorium
- Group 1: average arrears, tends to start the dunning process, rarely has field visits that result in payment
- Group 2: second highest arrears, tends to pay outside of moratorium, high chance of starting dunning process, tends to get disconnected
- Group 3: low arrears, rarely starts the dunning process
- Group 4: average arrears, has lots of field visits that result in payment
- Group 5: highest arrears, high moratorium indicator, highest chance of being disconnected

cluster s	Total 1-30		Total Balance 31-60	Total Balance 61-90				total_arre ars			winter_dunning_ starts	summer_dunning _starts
)	\$9.37	\$2.41	\$0.94	\$0.58	\$4.13	68%	\$16.86	0	0.01	0.1	0.28
	1	\$99.18	\$46.45	\$21.95	\$11.97	\$85.01	46%	\$252.59	0	0.34	4.61	7.18
	2	\$273.93	\$254.02	\$242.82	\$175.00	\$782.68	62%	\$1,553.46	0.05	0.61	2.6	6.13
;	3	\$7.69	\$1.55	\$0.70	\$0.38	\$2.79	36%	\$12.72	0	O	0.16	0.25
4	1	\$98.22	\$65.41	\$40.10	\$30.76	\$166.64	46%	\$370.38	1.37	, 0.37	4.51	7.12
!	5	\$301.64	\$386.93	\$320.44	\$186.95	\$5,630.61	65%	\$6,639.62	0.22	0.67	2.62	6.91





All Features for Clusters

- Group 0 & 3: lowest arrears groups, about 90% of all observations, difference in moratorium
- Group 1 & 4: average arrears, different dispersion in arrears
- Group 2 & 5: highest arrears, smallest group, younger accounts, 60-80% of customers identify as low income

clusters		total_arr ears	_	ebill_indi cator					moratorium_i ndicator	low_income_i ndicator	customer _age	calls_12 m_cp	_	financial_ass istance	college_ed ucation
(61631	\$17	71%	38%	9%	19%	27%	16	68%	9%	58	0.1	60%	4%	32%
•	8485	\$253	86%	46%	31%	39%	31%	10	46%	31%	49	1.5	79%	9%	20%
2	2 1542	\$1,553	88%	48%	65%	62%	32%	8	62%	65%	48	3.5	81%	31%	15%
3	3 53860	\$13	69%	38%	9%	18%	26%	17	36%	9%	58	0.1	59%	4%	29%
4	1174	\$370	88%	51%	31%	34%	28%	11	46%	31%	49	1.5	81%	9%	23%
Į	185	\$6,640	89%	42%	81%	70%	31%	9	65%	81%	49	5.3	83%	33%	15%





Internship Reflection



Beneficial Aspects

- Strengthened my coding skills
- Diversity in projects
 - Worked on 2 use cases, analytics challenges, and more
- Lots of learning opportunities

Improvements

- More opportunities to connect with other interns
- Personally taking the initiative to meet with people who have knowledge in something I'm struggling with





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Thank You

