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Quiz 3

1. A loan officer would be be able to make some sense from the explanations generated for the data scientist. If a loan officer has access to the HELOC data set, BRGC and LogRR will not be black box AIs to the loan officer. Additionally, BRGC and LogRR produces interpretable results where BRGC produces simple boolean rules for approving or rejecting a loan, and LogRR produces line graphs with simple patterns. BRGC and LogRR are not ideal to a loan officer as both do not provide much explainability in what data types are weighed when a decision is being made. A loan officer would not be able to explain why a customer's loan was rejected in much detail.

A customer would not be able to make sense of the explanations as customers would not have access to the HELOC data set and likely would not be familiar with the types of data on the data set itself. Even the algorithms used probably would not be familiar to the customer, so in this sense, both BRGC and LogRR are black boxes to the customer. Most importantly, a customer would want to know why a loan was rejected, even more so than a loan officer. Having a lack of explainability in why certain types of data are being used more than other types of data would not make a customer's situation better.

2. Profile of User id 2385:

0	
ExternalRiskEstimate	78
MSinceOldestTradeOpen	82
MSinceMostRecentTradeOpen	5
AverageMInFile	54
NumSatisfactoryTrades	33
NumTrades60Ever2DerogPubRec	0
NumTrades90Ever2DerogPubRec	0
PercentTradesNeverDelq	100
MSinceMostRecentDelq	0
MaxDelq2PublicRecLast12M	7
MaxDelqEver	8
NumTotalTrades	41
NumTradesOpeninLast12M	2
PercentInstallTrades	15
MSinceMostRecentInqexcl7days	0
NumInqLast6M	3
NumInqLast6Mexcl7days	3
NetFractionRevolvingBurden	21
NetFractionInstallBurden	11
NumRevolvingTradesWBalance	9
NumInstallTradesWBalance	3
NumBank2NatlTradesWHighUtilization	2

0	
PercentTradesWBalance	50
RiskPerformance	Good

Similar Profiles to User id 2385 with Weights:

	0	1	2	3	4
ExternalRiskEstimate	71	78	82	44	71
MSinceOldestTradeOpen	95	283	103	0	321
MSinceMostRecentTradeOpen	1	3	67	40	15
AverageMInFile	43	124	85	131	117
NumSatisfactoryTrades	33	33	1	57	60
NumTrades60Ever2DerogPubRec	0	0	0	3	0
NumTrades90Ever2DerogPubRec	0	0	0	1	0
PercentTradesNeverDelq	100	100	50	68	100
MSinceMostRecentDelq	0	0	62	0	0
MaxDelq2PublicRecLast12M	7	7	6	0	7
MaxDelqEver	8	8	6	5	8
NumTotalTrades	41	37	3	63	60
NumTradesOpeninLast12M	4	1	0	0	0
PercentInstallTrades	17	19	0	32	10
MSinceMostRecentInqexcl7days	0	3	0	0	0
NumInqLast6M	4	1	0	1	2
NumInqLast6Mexcl7days	4	1	0	1	2
NetFractionRevolvingBurden	17	77	0	58	43
NetFractionInstallBurden	89	0	0	13	39
NumRevolvingTradesWBalance	7	18	0	17	27
NumInstallTradesWBalance	3	3	0	3	2
NumBank2NatlTradesWHighUtilization	1	16	0	4	8
PercentTradesWBalance	53	92	0	79	60
RiskPerformance	Bad	Bad	Bad	Bad	Bad
Weight	0.733556	0.0681551	0.0782045	0.0223925	0.0976921

How Similar Prototypical Users are to id 2385

	0	1	2	3	4
ExternalRiskEstimate	0.59	1.00	0.74	0.08	0.59
MSinceOldestTradeOpen	0.90	0.19	0.84	0.51	0.14
MSinceMostRecentTradeOpen	0.85	0.92	0.08	0.25	0.67
AverageMInFile	0.71	0.12	0.39	0.09	0.14

	0	1	2	3	4
NumSatisfactoryTrades	1.00	1.00	0.22	0.32	0.28
NumTrades60Ever2DerogPubRec	1.00	1.00	1.00	0.08	1.00
NumTrades90Ever2DerogPubRec	1.00	1.00	1.00	0.08	1.00
PercentTradesNeverDelq	1.00	1.00	0.09	0.22	1.00
MSinceMostRecentDelq	1.00	1.00	0.08	1.00	1.00
MaxDelq2PublicRecLast12M	1.00	1.00	0.69	0.08	1.00
MaxDelqEver	1.00	1.00	0.21	0.09	1.00
NumTotalTrades	1.00	0.83	0.17	0.36	0.41
NumTradesOpeninLast12M	0.27	0.52	0.27	0.27	0.27
PercentInstallTrades	0.83	0.68	0.24	0.20	0.62
MSinceMostRecentInqexcl7days	1.00	0.08	1.00	1.00	1.00
NumInqLast6M	0.48	0.23	0.11	0.23	0.48
NumInqLast6Mexcl7days	0.48	0.23	0.11	0.23	0.48
NetFractionRevolvingBurden	0.87	0.13	0.47	0.26	0.45
NetFractionInstallBurden	0.10	0.72	0.72	0.94	0.43
NumRevolvingTradesWBalance	0.81	0.38	0.38	0.43	0.15
NumInstallTradesWBalance	1.00	1.00	0.08	1.00	0.42
NumBank2NatlTradesWHighUtilization	0.84	0.09	0.71	0.71	0.36
PercentTradesWBalance	0.91	0.26	0.21	0.40	0.73

Although User id 2385 had a risk performance predicted as good, 2385 had extremely similar results as bad applicants in the categories of NumTrades60Ever2DerogPubRec, NumTrades90Ever2DerogPubRec, and MSinceMostRecentInqexcl7days.

Profile of User id = 3:

0	
ExternalRiskEstimate	86
MSinceOldestTradeOpen	315
MSinceMostRecentTradeOpen	16
AverageMInFile	102
NumSatisfactoryTrades	18
NumTrades60Ever2DerogPubRec	1
NumTrades90Ever2DerogPubRec	0
PercentTradesNeverDelq	95
MSinceMostRecentDelq	64
MaxDelq2PublicRecLast12M	6
MaxDelqEver	5
NumTotalTrades	19
NumTradesOpeninLast12M	0

0	
PercentInstallTrades	53
MSinceMostRecentInqexcl7days	0
NumInqLast6M	5
NumInqLast6Mexcl7days	2
NetFractionRevolvingBurden	0
NetFractionInstallBurden	0
NumRevolvingTradesWBalance	1
NumInstallTradesWBalance	1
NumBank2NatlTradesWHighUtilization	0
PercentTradesWBalance	29
RiskPerformance	Good

Similar Profiles to User id 3 with Weights:

	0	1	2	3	4
ExternalRiskEstimate	72	0	81	72	69
MSinceOldestTradeOpen	156	383	291	110	428
MSinceMostRecentTradeOpen	2	383	42	7	3
AverageMInFile	53	383	135	63	94
NumSatisfactoryTrades	16	1	6	12	49
NumTrades60Ever2DerogPubRec	2	1	0	1	0
NumTrades90Ever2DerogPubRec	0	1	0	1	0
PercentTradesNeverDelq	89	100	67	92	100
MSinceMostRecentDelq	50	0	77	52	0
MaxDelq2PublicRecLast12M	6	6	5	6	7
MaxDelqEver	5	8	6	2	8
NumTotalTrades	24	1	6	13	23
NumTradesOpeninLast12M	1	0	0	1	3
PercentInstallTrades	37	100	50	54	8
MSinceMostRecentInqexcl7days	0	0	0	0	0
NumInqLast6M	0	1	0	3	4
NumInqLast6Mexcl7days	0	1	0	3	4
NetFractionRevolvingBurden	29	0	17	0	50
NetFractionInstallBurden	50	0	0	0	0
NumRevolvingTradesWBalance	2	0	2	0	11
NumInstallTradesWBalance	2	0	0	1	2
NumBank2NatlTradesWHighUtilization	1	0	0	0	10
PercentTradesWBalance	44	0	67	25	46
RiskPerformance	Bad	Bad	Bad	Bad	Bad

	0	1	2	3	4
Weight	0.0894829	0.0229659	0.390566	0.394776	0.102209

How Similar Prototypical Users are to id 3:

0	1	2	3	4	
ExternalRiskEstimate	0.62	0.06	0.84	0.62	0.56
MSinceOldestTradeOpen	0.28	0.58	0.82	0.19	0.40
MSinceMostRecentTradeOpen	0.91	0.08	0.84	0.94	0.92
AverageMInFile	0.67	0.10	0.76	0.73	0.94
NumSatisfactoryTrades	0.89	0.37	0.49	0.70	0.16
NumTrades60Ever2DerogPubRec	0.26	1.00	0.26	1.00	0.26
NumTrades90Ever2DerogPubRec	1.00	0.13	1.00	0.13	1.00
PercentTradesNeverDelq	0.61	0.66	0.10	0.78	0.66
MSinceMostRecentDelq	0.63	0.12	0.66	0.68	0.12
MaxDelq2PublicRecLast12M	1.00	1.00	0.21	1.00	0.21
MaxDelqEver	1.00	0.26	0.64	0.26	0.26
NumTotalTrades	0.58	0.14	0.24	0.52	0.64
NumTradesOpeninLast12M	0.40	1.00	1.00	0.40	0.06
PercentInstallTrades	0.58	0.21	0.90	0.97	0.22
MSinceMostRecentInqexcl7days	1.00	1.00	1.00	1.00	1.00
NumInqLast6M	0.05	0.09	0.05	0.29	0.54
NumInqLast6Mexcl7days	0.29	0.54	0.29	0.54	0.29
NetFractionRevolvingBurden	0.22	1.00	0.41	1.00	0.07
NetFractionInstallBurden	0.08	1.00	1.00	1.00	1.00
NumRevolvingTradesWBalance	0.78	0.78	0.78	0.78	0.09
NumInstallTradesWBalance	0.33	0.33	0.33	1.00	0.33
NumBank2NatlTradesWHighUtilization	0.77	1.00	1.00	1.00	0.08
PercentTradesWBalance	0.51	0.28	0.19	0.84	0.47

Although User id 3 had a risk performance predicted as good, 3 had similar results as bad applicants in terms of NumTrades90Ever2DerogPubRec, and MaxDelq2PublicRecLast12M. User ID had extremely similar results as bad applicants in terms of MSinceMostRecentInqexcl7days, NetFractionInstallBurden, and NumBank2NatlTradesWHighUtilization.

3. For User id 2344, a loan would have been accepted if that user's ExternalRiskEstimate score was 5.240000 points higher (PN score of 77.240000 needed), and if that user's AverageMInFile score was 13.940000 points higher (PN score of 68.940000 needed). ExternalRiskEstimate is weighted at around 0.5 for importance, while AverageMInFile is weighted slightly lower at around 0.4 for importance.

A loan for user 449 would have been accepted if that user's ExternalRiskEstimate score was 9.530000 points higher (PN score of 86.530000 needed), the AverageMInFile score was 7.950000 points higher (PN score of 117.950000 needed), and the NumSatisfactoryTrades score was 2.230000 points higher (PN score of 12.230000 needed). ExternalRiskEstimate is weighted at around 1.0 for importance and is overwhelmingly the most important feature. AverageMInFile and NumSatisfactoryTrades are about the same in importance with the former weighted around 0.2 and the later weighted around 0.2 but marginally lower.

User id 1168's loan could have been accepted if that user's ExternalRiskEstimate score was 7.030000 points higher (PN score of 68.030000 needed), and if that user's AverageMInFile score was 20.300000 points higher (PN score of 101.300000 needed). ExternalRiskEstimate is weighted at around 0.7 for importance, while AverageMInFile is weighted slightly lower at around 0.6 for importance.

4. I used the BRCG classification method for the data scientist, the loan officer, and the customer. A modified notebook for BRCG is in the Quiz3 directory.

5. Prototypical explanations are helping with understanding the survey responses in that they summarize the kinds of of people responding. ProtoDash selects a handful of respondents that are the most representative of thousands of respondents. Simply generating an average of all responses throws away correlations from minorities (statistical outliers) that would be possibly of interest, such as people living off of social security or have more than $5000 in savings. Generating an average of responses would not be as explainable either.

Additionally, prototypical explanations are highly useful in that they can list how well prototypes generated from one set of data represent correlations from another set of data. The better a representation is in this case, the stronger the correlation is. The Early Childhood questionnaire was represented the best, so it can be said that early childhood environments contribute the most to income.

The roles that the notebook is best suited for is sociological research and policy makers. Sociologists are interested in how different groups of people are effected by society, so generating prototypes as mentioned earlier, would be useful to them. In addition, a policy maker would want to make sure that policies do not negatively effect outliers. The questionnaires of Physical Functioning and Acculturation are not too far behind in representation as the Early Childhood one, so a sociologist might want to study physical functioning and acculturation in how they relate to income. A sociologist or policy maker most likely understands data more than AI models, so ProtoDash would be the most suitable in explainability. A policy maker's decisions definitely need to be trustworthy, so having explainable models for decisions are critical.

6. The problem's goal is to determine non-negative weights of importance in data for building a small set of prototypes. This involves maximize the scoring function, f(.), which measures quality, relevance, and information of particular data points. Linear correlations are created for all features in the space by transforming data into higher dimensions through a cross product. If a potential linear correlation is a real number, a maximum mean discrepancy is determined from the correlation. An approximate population mean can start to be determined. A subset of the source data is considered in

trying to minimize the finite sample maximum mean discrepancy. The MMD is minimized by taking into account weights, the kernel, and the target. Indexes of elements are created, and terms in this group not depending on the subset and weight are removed. A point-wise empirical evaluation of the population mean is made, and an index set is created that corresponds to a weight with bounds. An optimal set is derived from the index set by maximization at a certain location via a complex function. Prototype weights are then determined from that complex function.

ProtoGreedy is similar to L2C, but differs in that it determines unequal non negative weights in prototypes, unlike L2C. ProtoGreedy is also weakly submodular even with added constraints. ProtoGreedy works by adding weights to an empty set that are simply an argmax and that are shared by other points of data in the source. A subset from the weights are taken again that are an element of the smallest close set that are non negative. A complex weight function and list is returned. ProtoDash is similar to ProtoGreedy, but it is more conservative in choosing weights by using a maximum mean discrepancy and by setting bounds of correlations used in determining weights by using a gradient.