



Risk Rules Evaluation

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December 26, 2016

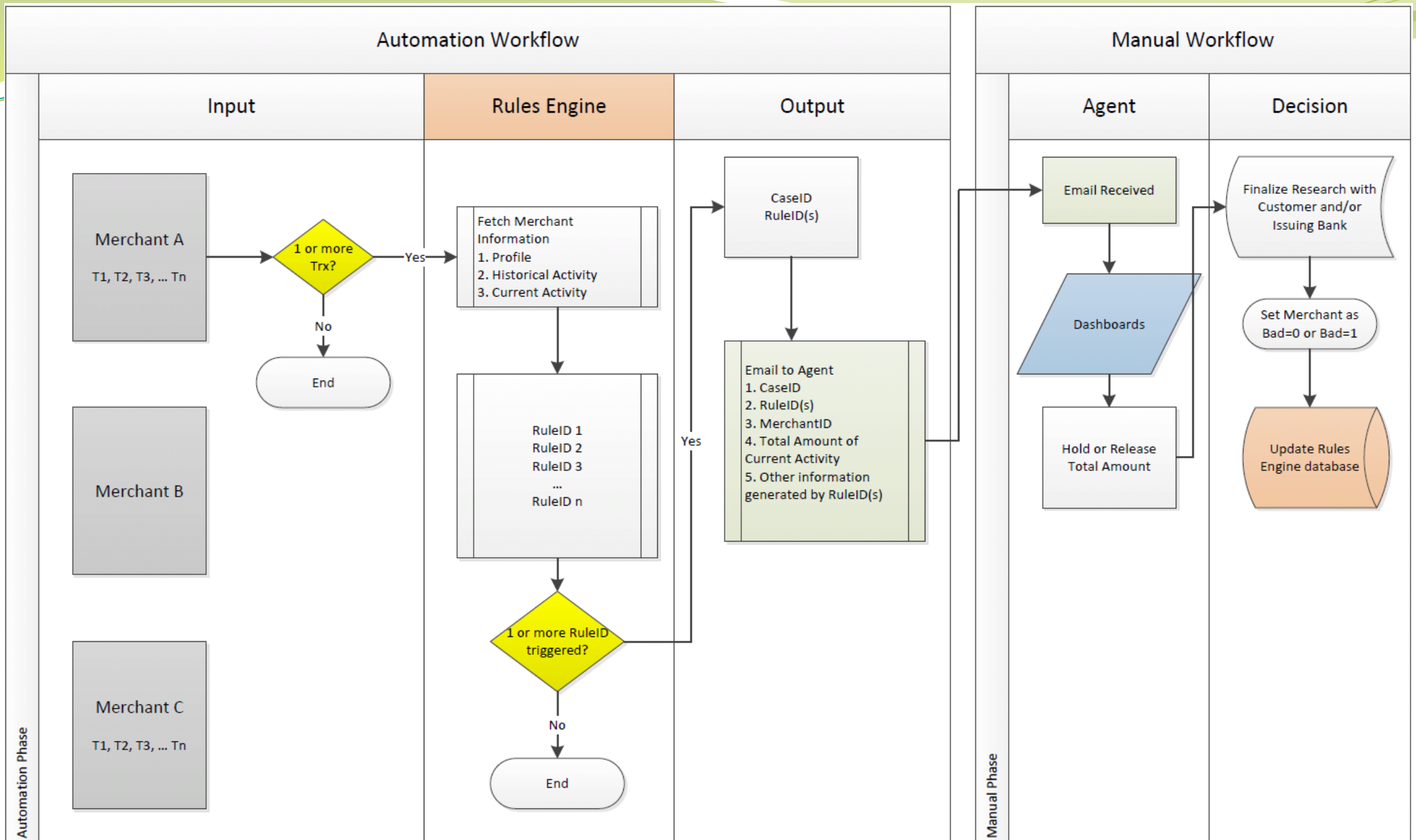


Agenda

- Tasks Assigned
- Process Workflow Assumptions
- Data Set
- Definitions of Rule Performance
- Dashboard Mockups
- Overall decision making process
- Q&A

Tasks Assigned

- Create a reasonable definition(s) of rule performance
- Build a mockup of a dashboard(s) that tracks rules performance (by rule and by RiskAlertCategory) in whatever way you think is appropriate (there may be multiple ways to assess performance).
- Assess the overall decision making process (which includes Risk Agents' decisions).



Data Set

Rules Category Table

[RuleId] - a number that uniquely identifies a rule
[RiskAlertCategory] – risk alert category name

Rules Table

[CaseId] – a number that uniquely identifies a case
[RuleID] – a number that uniquely identifies a rule

Cases Table

[MerchantId] – a number that uniquely identifies a merchant
[CaseId] – a number that uniquely identifies a case
[AlertDate] – date when the case was generated
[Held] – indicates whether funds for the merchant's current activity were put on hold (1) or not (0) by the Risk Agent who reviewed the Case
[Amount] – total amount of the merchant's current activity (whether held or not)
[BadMerch] – indicates the final outcome: did the merchant eventually turn out bad (1=fraudulent or led to losses) or not (0)

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/****** cases rule query example *****/
```

```
select convert(decimal(10,2),sum(data.[amount])) sumAmt,  
convert(decimal(10,2),avg(data.[amount])) avgAmt,  
count(*) countAmt  
from  
(select  
  c.[caseID] ,r.[ruleID] ,t.[ruleType] ,c.[amount]  
  from [ReportServer$SQLBUSPLAN].[dbo].[rules__t] as r  
  inner join [ReportServer$SQLBUSPLAN].[dbo].[ruleCategories__t] as t  
  on r.[ruleID] = t.[ruleID]  
  inner join [ReportServer$SQLBUSPLAN].[dbo].[cases__t] as c  
  on r.[caseID] = c.[caseID]  
  where r.[ruleID] = 9 and c.[badMerch] = 1 and c.[held] = 1) as data
```

Definition of Rules Performance

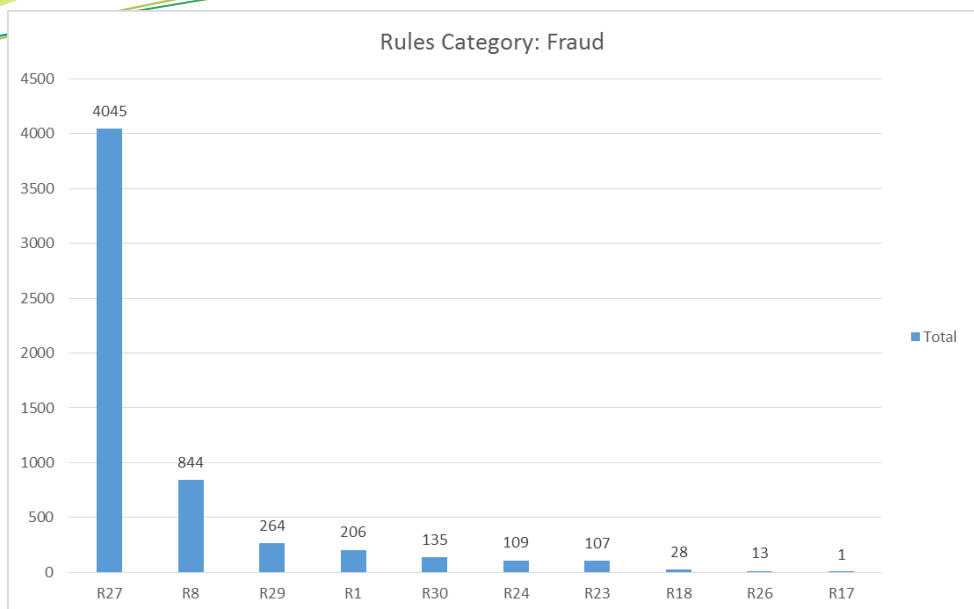
- Generate **Count of Case Triggers** by RuleID within timeframe
 - Segment RuleID's by RiskAlertCategory and by Day
 - Monitor usage overtime
 - A rule that is seldom invoked may be too narrowly defined
 - Conversely, a rule that is invoked more often may be too broadly defined and lead to lower detection power.
- Generate Confusion Matrix per RuleID
 - **True Positives** (Sensitivity Test) - If a merchant is bad=1, how often will the RiskAgent hold (hold=1) the Amount?
 - **True Negatives** (Specificity Test) – If merchant is bad=0, how often will the RiskAgent not hold (hold=0) the Amount?
 - **False Positives** (1 – Specificity) - If merchant is bad=0, how often will the RiskAgent hold (hold=1) the Amount? *Misclassified as potentially fraud*
 - **False Negatives** (1 – Sensitivity) – If merchant is bad=1, how often will the RiskAgent not hold (hold=0) the Amount? *Misclassified as non-fraud*

Note: For Confusion Matrix, we generally want to maximize True Positives/True Negatives and minimize False Positives/False Negatives

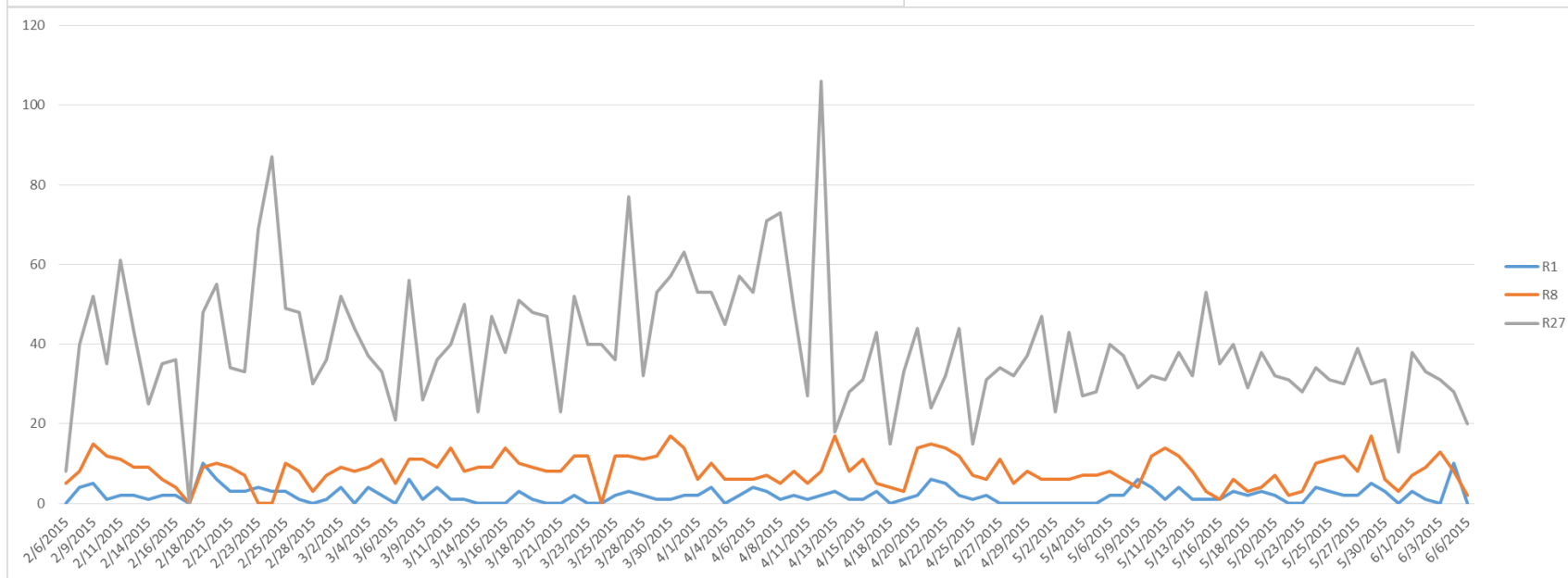
Definition of Rules Performance

- For each RuleID in Fraud and Financial Risk categories:
 - Generate Financial Losses Correctly Mitigated
 - Generate Financial Losses Incorrectly Mitigated
 - Generate Ratio of Losses (correct/incorrect)
 - Generate Rank Analysis
- For each RuleID in Compliance category:
 - Generate Financial Revenue Correctly Released
 - Generate Financial Revenue Incorrectly Released
 - Generate Ratio of Revenues (correct/incorrect)
 - Generate Rank Analysis

Dashboard (Case Triggers)

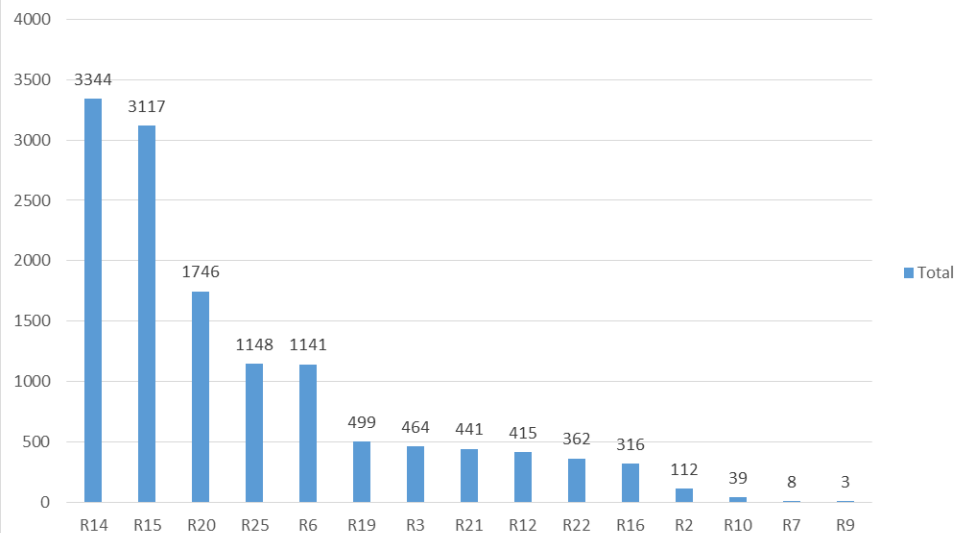


- Total Case Triggers by RuleID
- Filter by RiskAlertCategory
- Filter by Date Range
- Filter by Merchant ID
- Filter by Device, by IP Address
- Filter by Checkpoints (at what point in verification stage when Rule is triggered: Acquiring Bank, Payment Brands, Issuing Bank, etc.)
- Display Average and Total Processing Time
- Distribution of Events by Geography

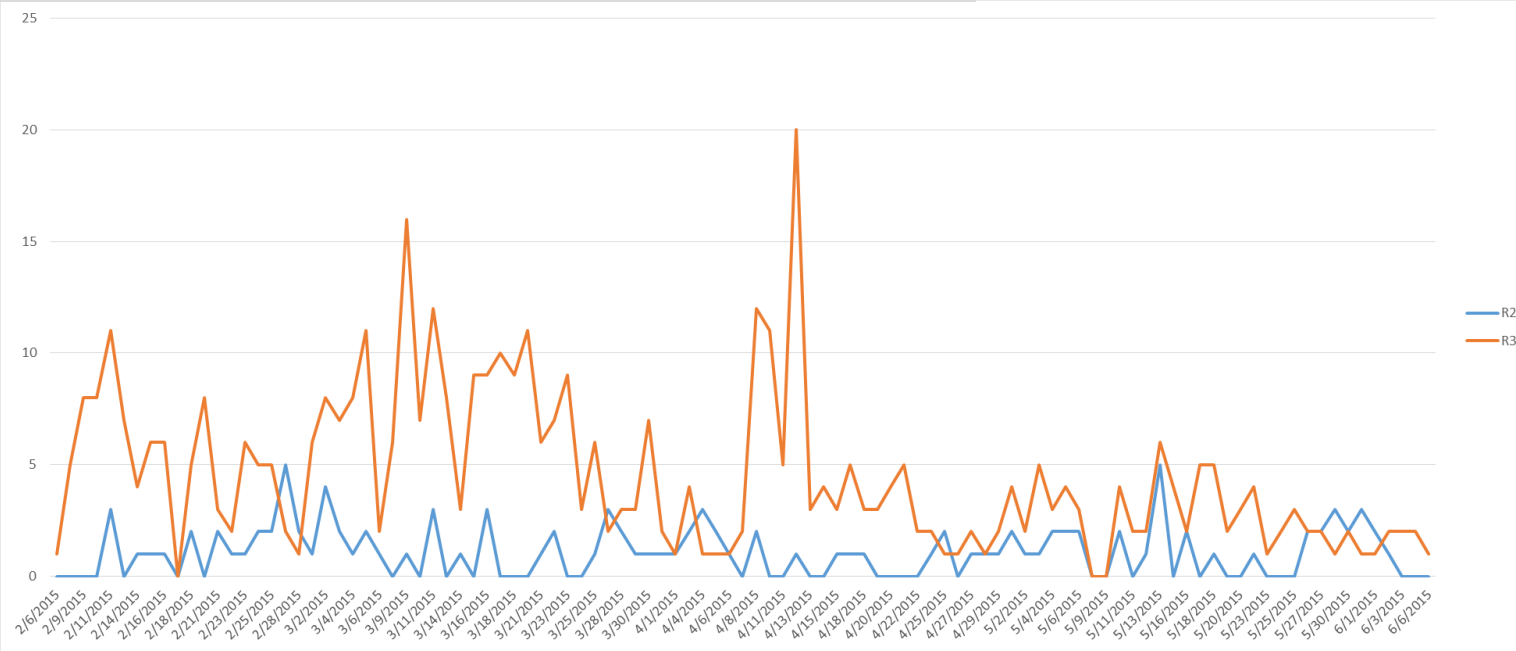


Dashboard (Case Triggers)

Rules Category: Financial Risk



- Total Case Triggers by RuleID
- Filter by RiskAlertCategory
- Filter by Date Range
- Filter by Merchant ID
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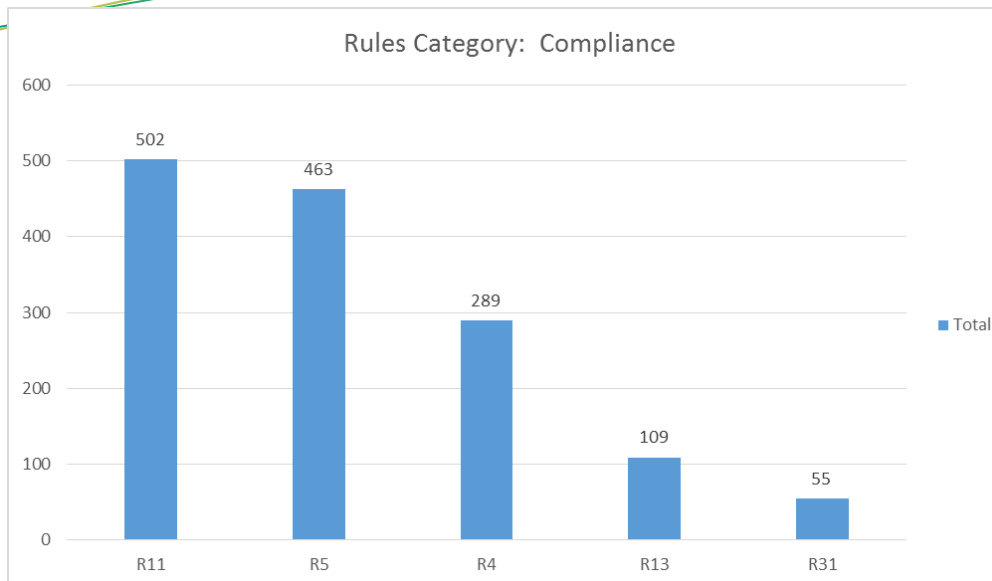


Views by Day, Week or Month

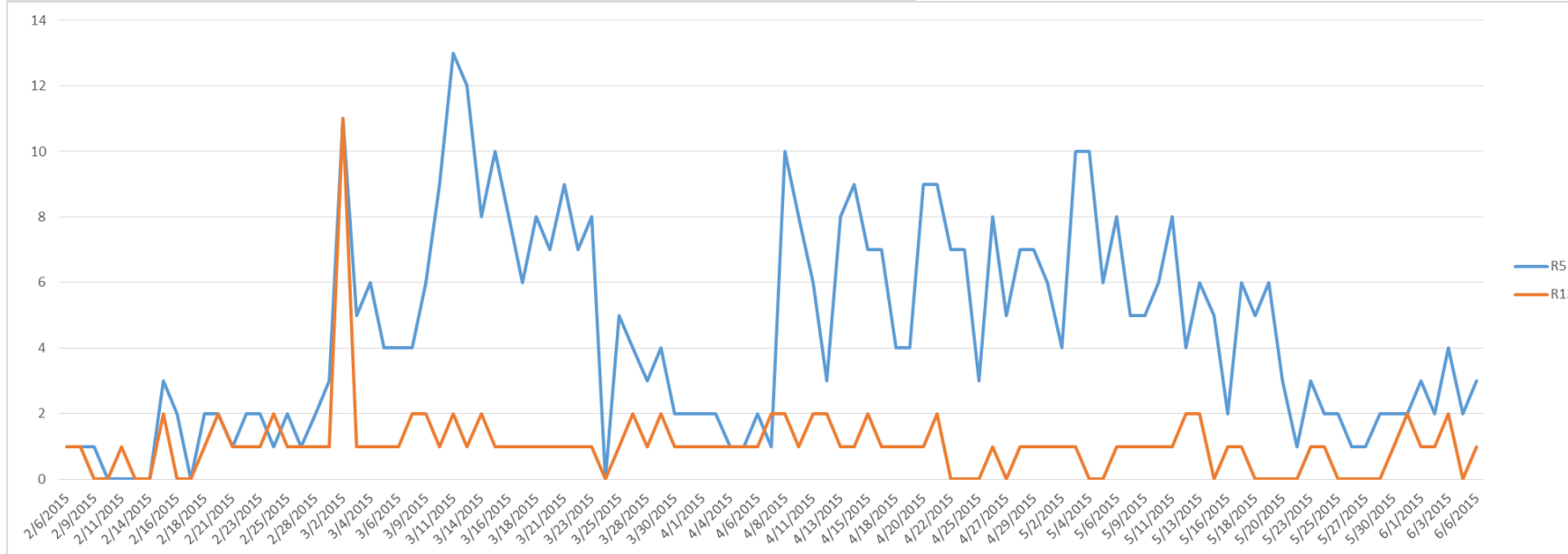
Drill-down view by Hour

Filter by RuleID

Dashboard (Case Triggers)



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Views by Day, Week or Month

Drill-down view by Hour

Filter by RuleID

Dashboard (Confusion Matrix)

- Example of Confusion Matrix for Rule ID 23 (Fraud) and ID 11 (Compliance)

Count

	held=1	held=0	Total
bad=1	48	30	78
bad=0	3	26	29
Total	51	56	107

Average Amount

	held=1	held=0	Total
bad=1	1,352.55	625.74	1,073.00
bad=0	1,515.87	4,144.77	3,872.81
Total	1,362.15	2,259.57	1,831.83

Sensit.	62%
Specif.	90%
PV+	94%
PV-	46%
F+ Rate	10%
F- Rate	38%
% Held	48%
% Not Held	52%

Count

	held=1	held=0	Total
bad=1	27	26	53
bad=0	86	363	449
Total	113	389	502

Average Amount

	held=1	held=0	Total
bad=1	24,891.88	18,399.86	21,707.12
bad=0	33,787.79	24,414.98	26,210.22
Total	31,662.22	24,012.94	25,734.79

Sensit.	51%
Specif.	81%
PV+	24%
PV-	93%
F+ Rate	19%
F- Rate	49%
% Held	23%
% Not Held	77%

Dashboard (Rank Analysis Table)

- Risk Alert Category: Fraud

- Rules Performance in aiding Agent's decision to hold transaction given Merchant is truly bad
- Assumption: Underlying algorithm may use predictive models (LR, ANN); Training data set has more fraud cases than non-fraud to build model to detect fraud patterns

RuleID	Sensitivity	F+ Rate	delta	rank1	Case Triggers	Losses Correctly Mitigated	Losses Incorrectly Mitigated	Ratio of Losses	rank2	rank3	sumRank	Overall Rank
17 - Fraud*	0%	#DIV/0!	#DIV/0!		1	\$0K	\$0K	0.00				2
23 - Fraud	62%	10%	51%	1	107	\$65K	\$5K	14.28	2	6	9	1
1 - Fraud	79%	34%	45%	2	206	\$474K	\$67K	7.10	3	3	8	3
18 - Fraud	95%	57%	38%	3	28	\$13K	\$0K	1283200.00	1	7	11	7
30 - Fraud	75%	45%	30%	4	135	\$87K	\$215K	0.40	8	5	17	5
27 - Fraud	34%	5%	29%	5	4045	\$725K	\$766K	0.95	6	2	13	8
26 - Fraud	50%	60%	-10%	9	13	\$9K	\$9K	0.94	7	8	24	4
8 - Fraud	100%	100%	0%	6	844	\$1,005K	\$576K	1.75	5	1	12	6
29 - Fraud	94%	95%	-1%	7	264	\$118K	\$42K	2.81	4	4	15	9
24 - Fraud	0%	3%	-3%	8	109	0	\$197K	0.00	9	9	26	

Preferred

* too narrow, rule may not actually measure what it was intended to truly measure because it was designed incorrectly, or configured incorrectly, or missing set of criterias, etc. Candidate for review

Dashboard (Rank Analysis Table)

- Risk Alert Category: Financial Risk

- Rules Performance in aiding Agent's decision to hold transaction given Merchant is truly bad
- Assumption: Underlying algorithm may use anomaly detection to signal risk; Training data set has more non-fraud cases than fraud to build model that detects anomalies (deviations from normal behavior)

RuleID	Sensitivity	F+ Rate	delta	rank1	Case Triggers	Losses Correctly Mitigated	Losses Incorrectly Mitigated	Ratio of Losses	rank2	rank3	sumRank	Overall Rank
2 - Financial Risk	56%	6%	49%	2	112	\$10K	\$35K	0.27	13	13	28	10
3 - Financial Risk	26%	6%	20%	10	464	\$252K	\$195K	1.29	8	5	23	8
6 - Financial Risk	58%	18%	39%	5	1141	\$1,807K	\$2,651K	0.68	11	1	17	4
7 - Financial Risk*	33%	0%			8	\$2K	0					
9 - Financial Risk*	67%	#DIV/0!			3	\$3K	\$0K					
10 - Financial Risk	43%	28%	15%	12	39	\$22K	\$15K	1.44	7	12	31	12
12 - Financial Risk	46%	10%	36%	7	415	\$109K	\$33K	3.29	3	9	19	6
14 - Financial Risk	30%	4%	25%	9	3344	\$702K	\$460K	1.53	6	4	19	6
15 - Financial Risk	52%	9%	44%	4	3117	\$1,293K	\$600K	2.16	5	2	11	3
16 - Financial Risk	72%	11%	61%	1	316	\$218K	\$54K	4.05	2	6	9	1
19 - Financial Risk	31%	3%	28%	8	499	\$188K	\$41K	4.54	1	8	17	4
20 - Financial Risk	60%	11%	48%	3	1746	\$1,131K	\$500K	2.26	4	3	10	2
21 - Financial Risk	16%	5%	11%	13	441	\$40K	\$35K	1.17	9	11	33	13
22 - Financial Risk	45%	8%	37%	6	362	\$60K	\$83K	0.72	10	10	26	9
25 - Financial Risk	22%	6%	16%	11	1148	\$215K	\$561K	0.38	12	7	30	11

Preferred

Preferred

* too narrow, rule may not actually measure what it was intended to truly measure because it was designed incorrectly, or configured incorrectly, or missing set of criterias, etc. Candidate for review

Dashboard (Rank Analysis Table)

- Risk Alert Category: Compliance

- Rules Performance in aiding Agent's decision to not hold transaction given Merchant is truly not bad
- Assumption: Algorithm may use set of boolean logic (If/Then/Else constructs), Decision Trees

RuleID	Specificity	F- Rate	delta	rank1	Case Triggers	Revenue Correctly Released	Revenue Incorrectly Released	Ratio of Gains	rank2	rank3	sumRank	Overall Rank
4 - Compliance	99%	79%	20%	2	289	\$771K	\$30K	26.06	2	4	8	3
5 - Compliance	96%	85%	12%	3	463	\$8,933K	\$316K	28.25	1	1	5	1
11 - Compliance	81%	49%	32%	1	502	\$8,863K	\$478K	18.53	3	2	6	2
13 - Compliance	99%	91%	8%	4	109	\$5,514K	\$2,557K	2.16	4	3	11	4
31 - Compliance*	98%	#DIV/0!	#DIV/0!		55	\$60K	0	6009012.00				

Least Preferred

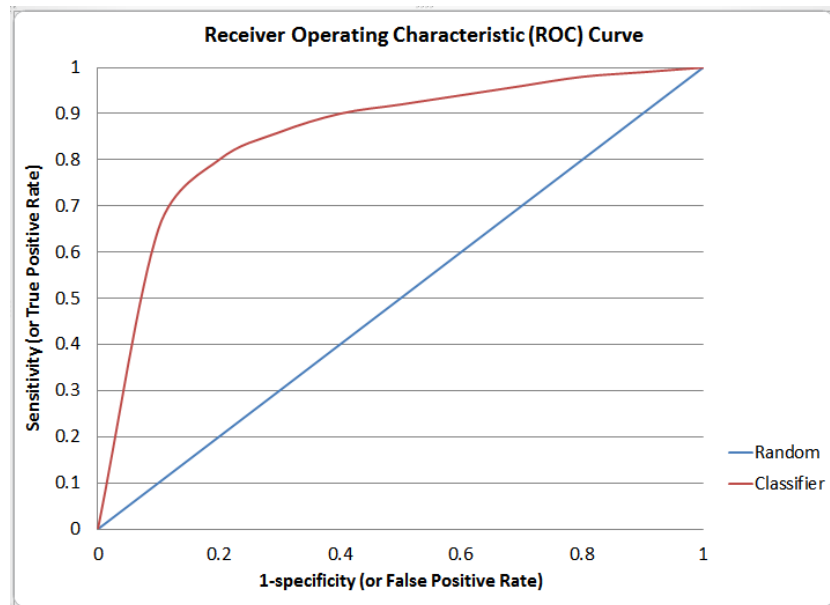
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Decision Making Process

- A Business Rule (BR) that is rarely invoked is a candidate for review:
 - Upon receiving such a rule, the Risk Agent (RA) should spend more time researching Case
 - Consider modifying the Business Rule
- A BR that is more often invoked is a candidate for review:
 - Upon receiving such a rule, the Risk Agent (RA) should spend more time researching Case
 - Business Rule could be too broadly defined, thus losing its detection power
- Consider the BR performance relative to others in its Class:
 - If RA receives Rule X for Case Y, compare X's relative rank to others within its class using the Rank Analysis Table. Spend less time reviewing cases with more favorable rankings, and vice versa.

Conclusion

- A BR that outputs binary classifiers can be modeled using Logistic Regression
- Run the BR against the same data set, but varying the thresholds
 - Determine optimal threshold using ROC curve.
 - If binary classifier is set to optimal threshold, then RA is likely to be in agreement with the output of the BR, hence spending less time researching.





Questions?