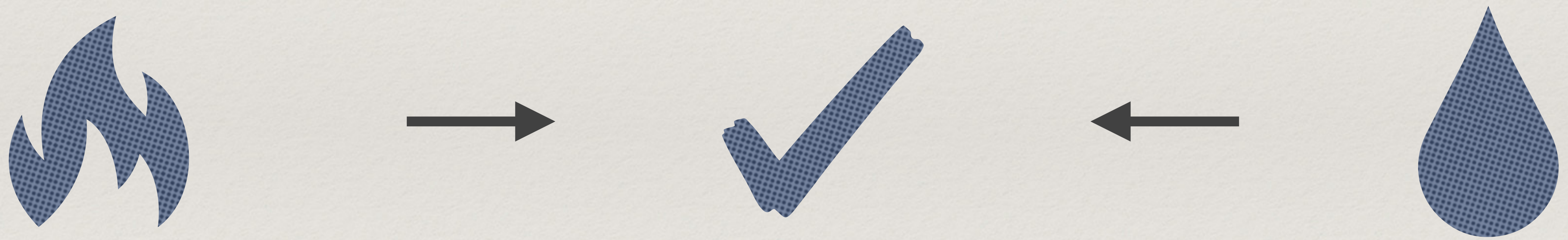
Lloyd Montgomery, The SEGAL Group

Sentiment Analysis as a tool to Define Customer Personas

Motivation

Motivation

Customers who Need Help → **Support Tickets to Coordinate Help** ← **Support Analysts Administering Help**



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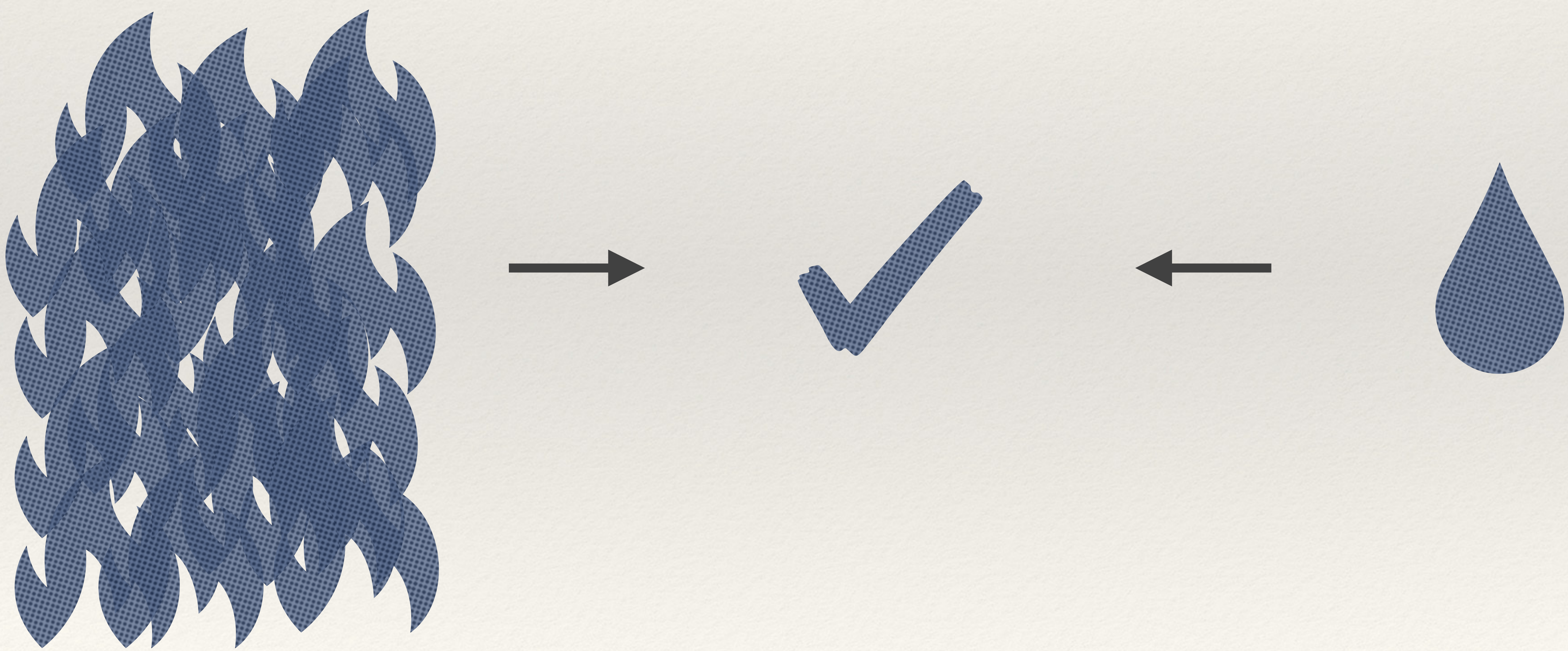

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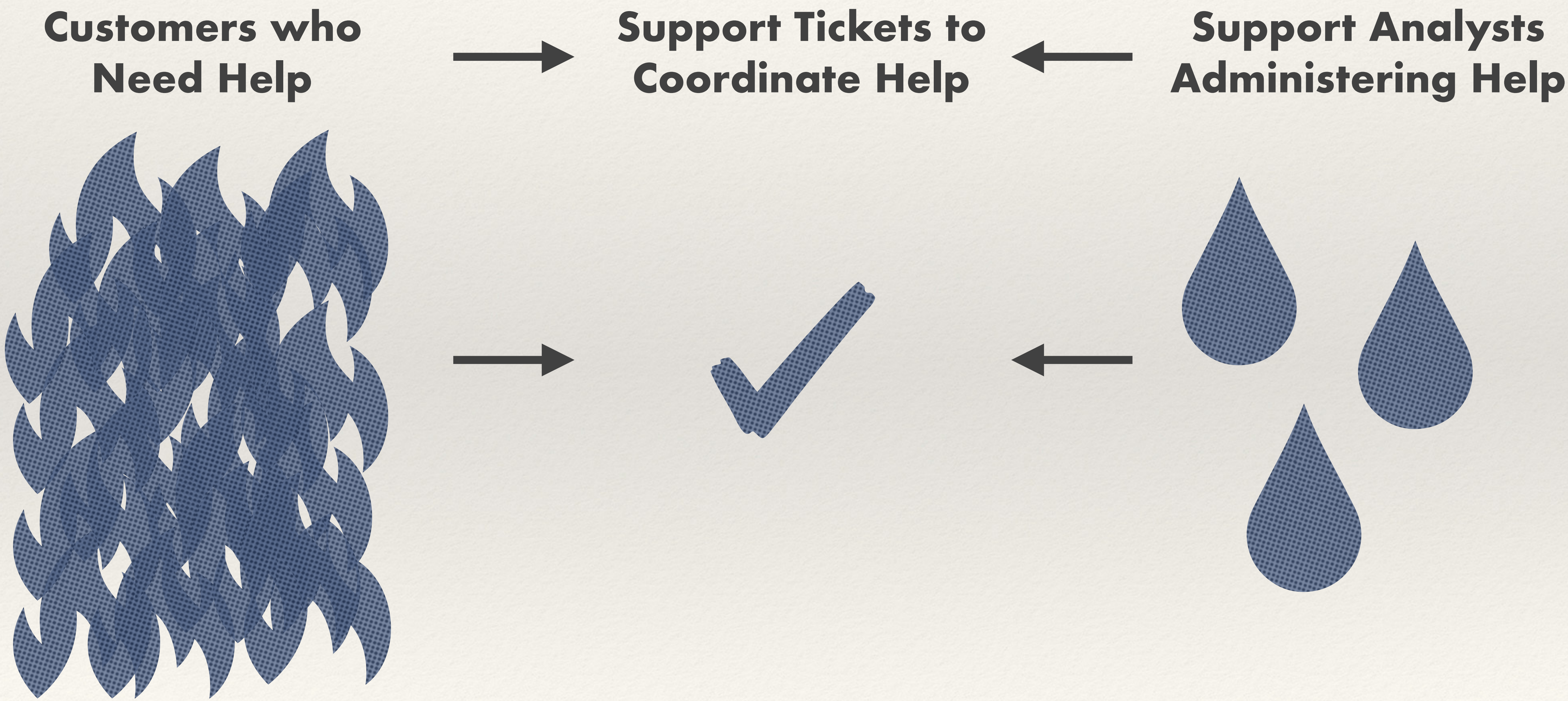
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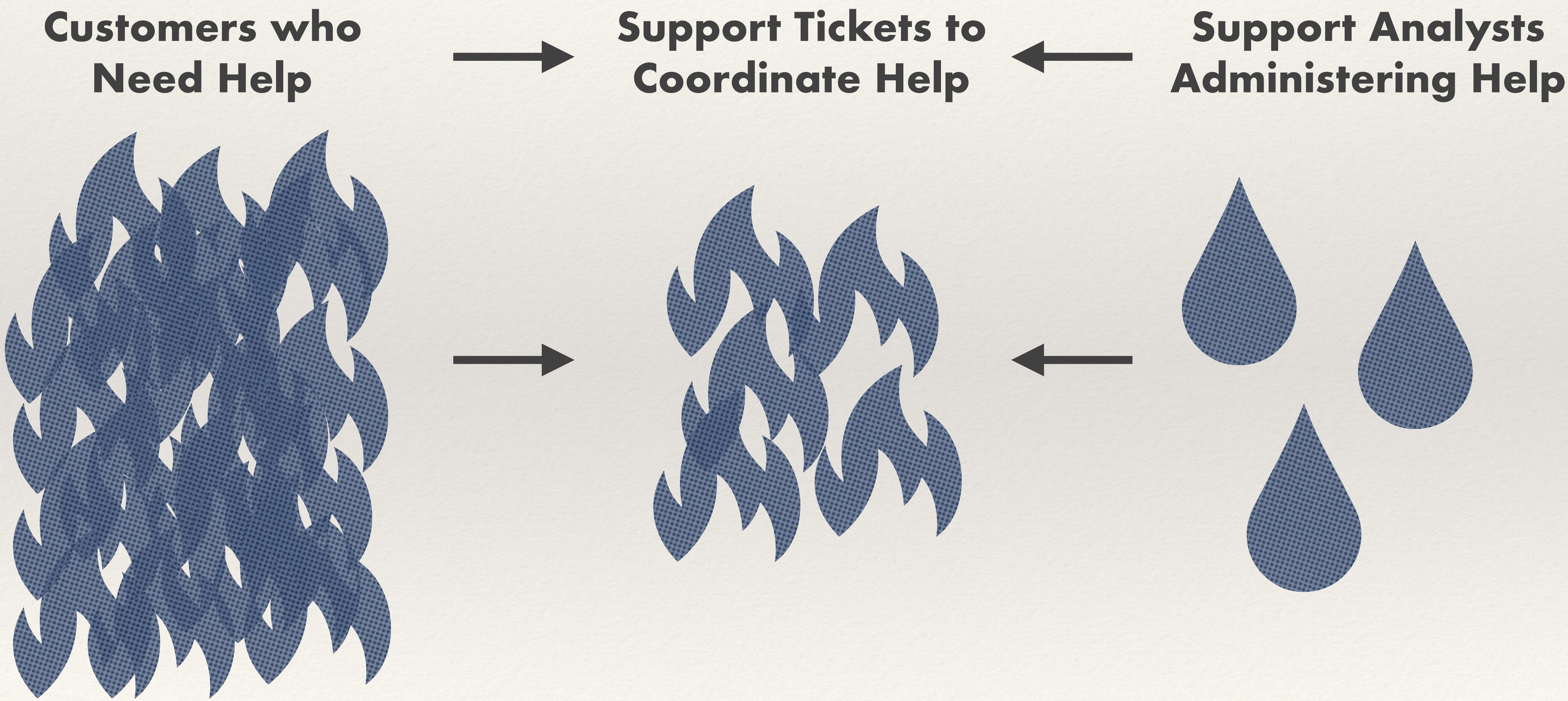
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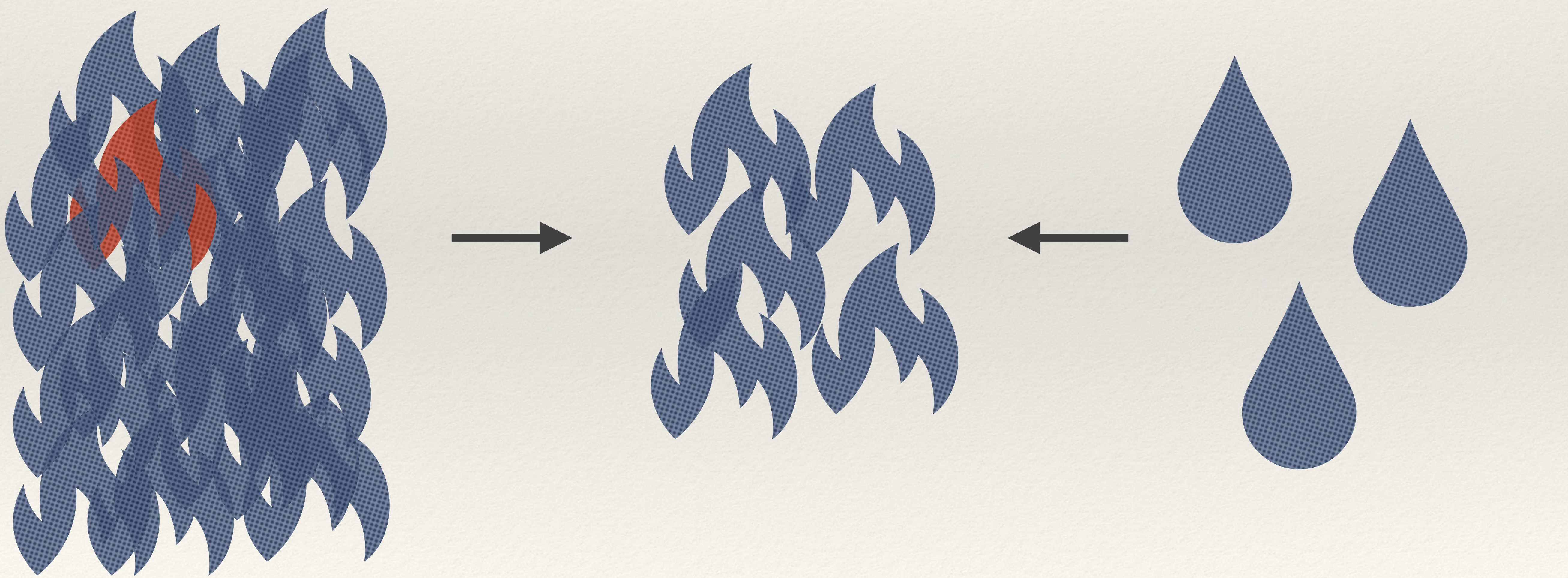

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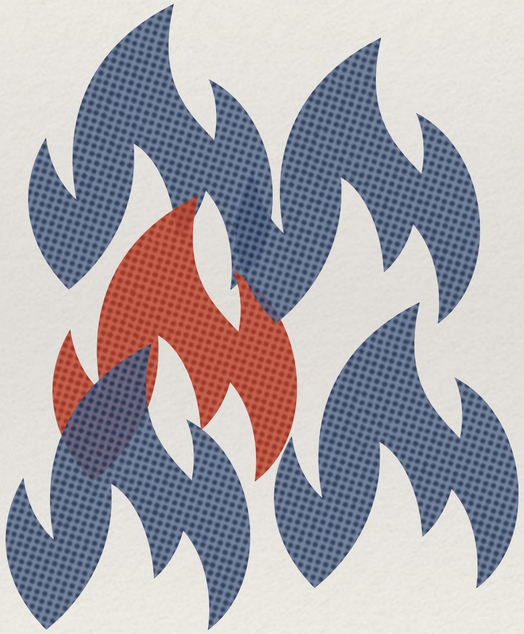

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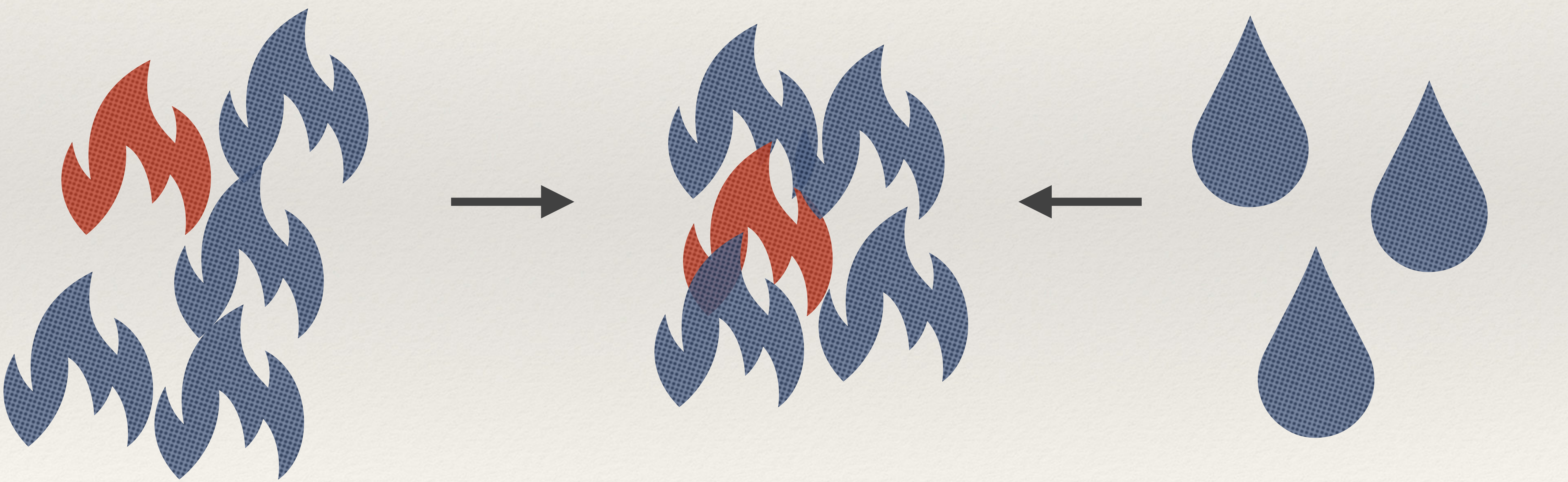

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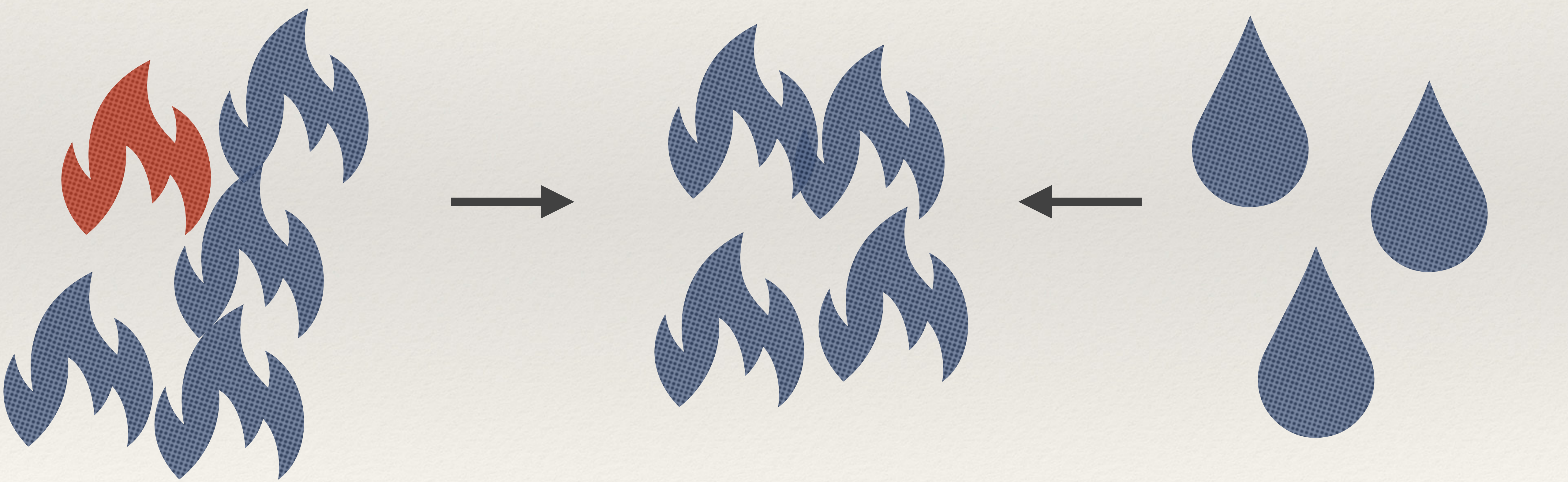


Research Questions

RQ 1. What are the features of a support-ticket model to best describe a customer escalation?

RQ 2. Can ML techniques that implement such a model assist in escalation management?

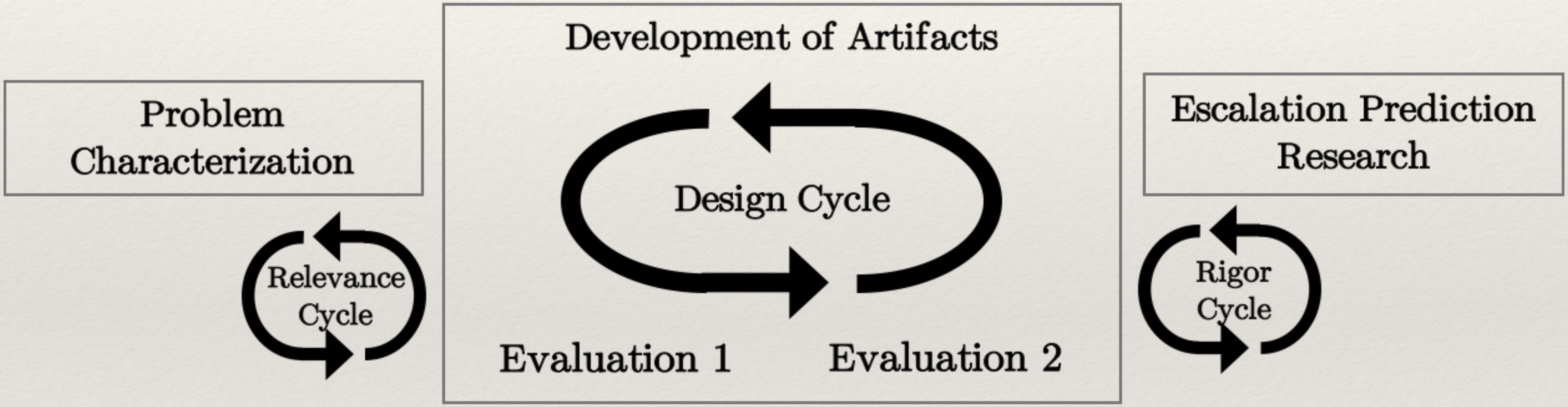
Results!

Context-based features from the perspective of the customer can capture elements of escalations

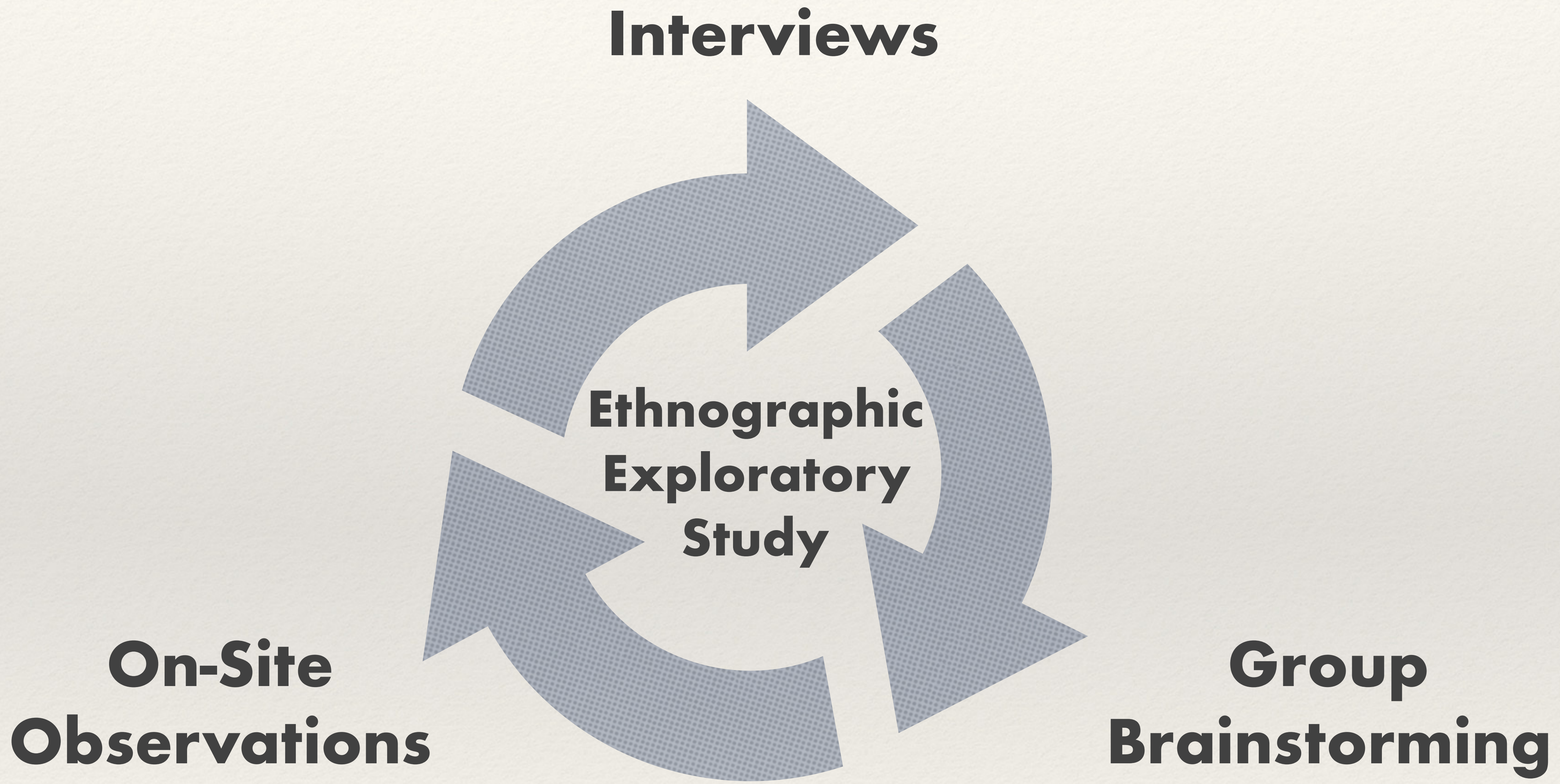
Yes! Machine learning applied to support ticket data can predict customer escalations

Methodology

Design Science Research



RQ1: Problem Characterization



Related Work

Customer Relationship Management

Support Ticket Automated Categorization

Escalation Prediction
(Bruckhaus & Madhavji)

Feature Engineering

Feature Engineering

Support Analysts **know their Customers**

Feature Engineering Facilitates the Transfer of **Domain-Specific Knowledge**

RQ1: Support Ticket Model Features

Basic Attributes

- Number of Entries
- Days Open
- Escalation Type
- Support Ticket Ownership Level

Customer Perception of Time

- Time until First Contact
- Average Support Response Time
- Difference in Average vs Expected Response Time
- Days Since Last Contact

Customer Perception of Process

- Number of Support people
- Number of Increases in Severity
- Number of Decreases in Severity
- Number of Sev4/Sev3/Sev2 to Sev1 Transitions

Customer Profile

- Number of Closed Support Tickets
- Number of Closed Escalations
- Escalation to Support Ticket Ratio
- Expectation of Support Response Time
- Number of Open Support Tickets
- Number of tickets opened in the last X months
- Number of tickets closed in the last X months
- Number of Escs opened in the last X months
- Number of Escs closed in the last X months
- Expected support response time given the last X months

RQ1: Support Ticket Model Features

Basic Attributes

- Number of Entries
- Days Open

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- Expectation of Support Response Time

RQ2: Machine Learning Model

Data Processing

2,500,000 Support Tickets
10,000 Escalations

Training

Random Forest Model

Testing

10-Fold Cross Validation

90/10 Split Each

Interpreting the Results

Confusion Matrix

RQ2: Machine Learning Model

Actual	Total	Predicted as	
		Escalation - No	Escalation - Yes
Escalation - No	2,557,730	2,072,496 (TN) 81.03%	485,234 (FP) 18.97%
Escalation - Yes	10,199	2,046 (FN) 20.06%	8,153 (TP) 79.94%

Accuracy	Recall	Precision	Summarization
80.49%	79.94%	1.65%	80.79%

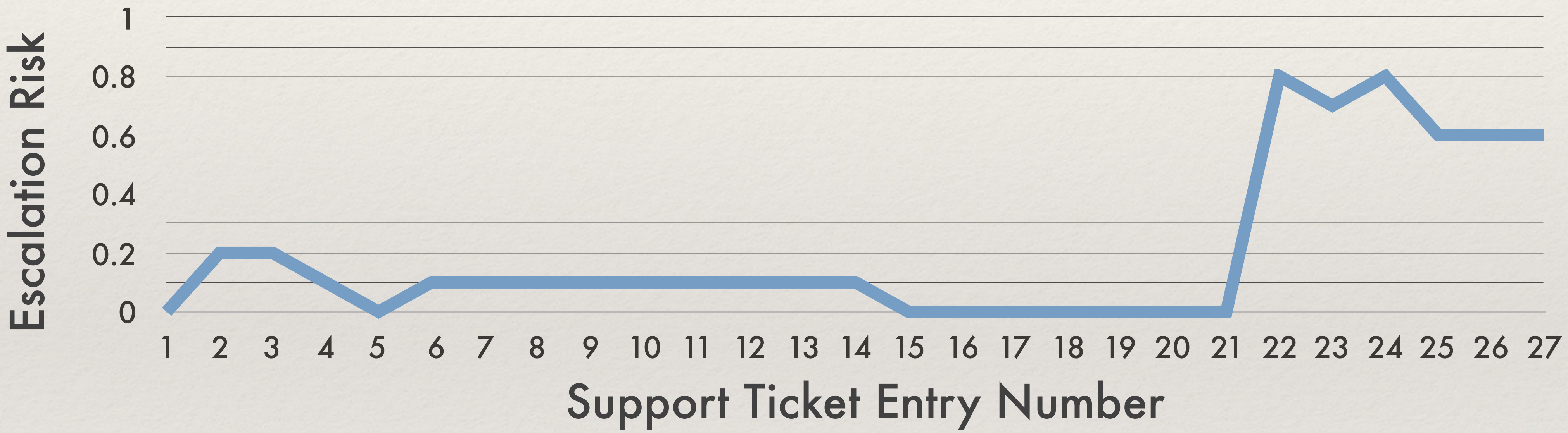
Model Evaluation 1

In-depth Analysis of Model Behaviour

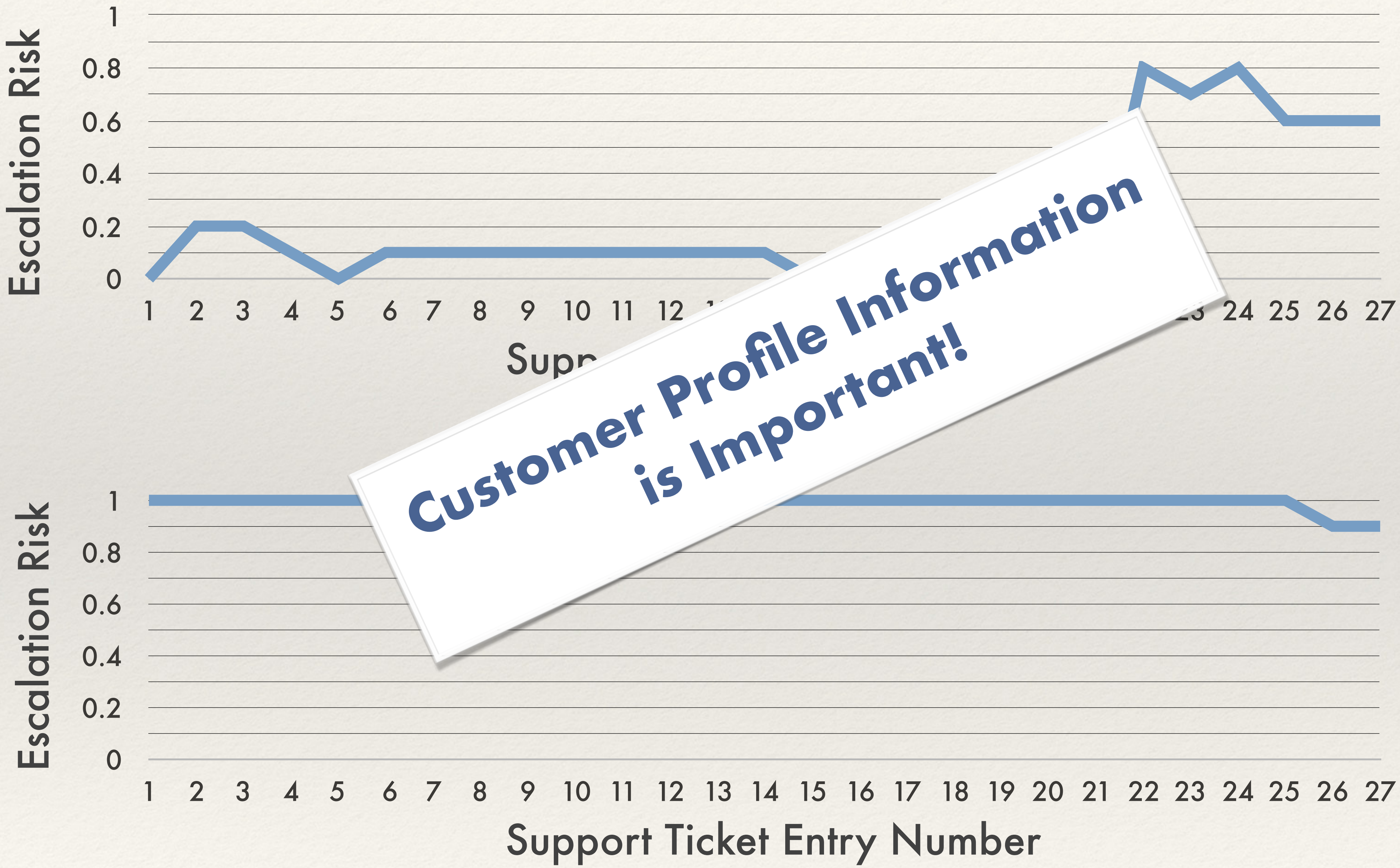
2 Hour Review of Escalations

Graphing Escalation Risk for Support Tickets

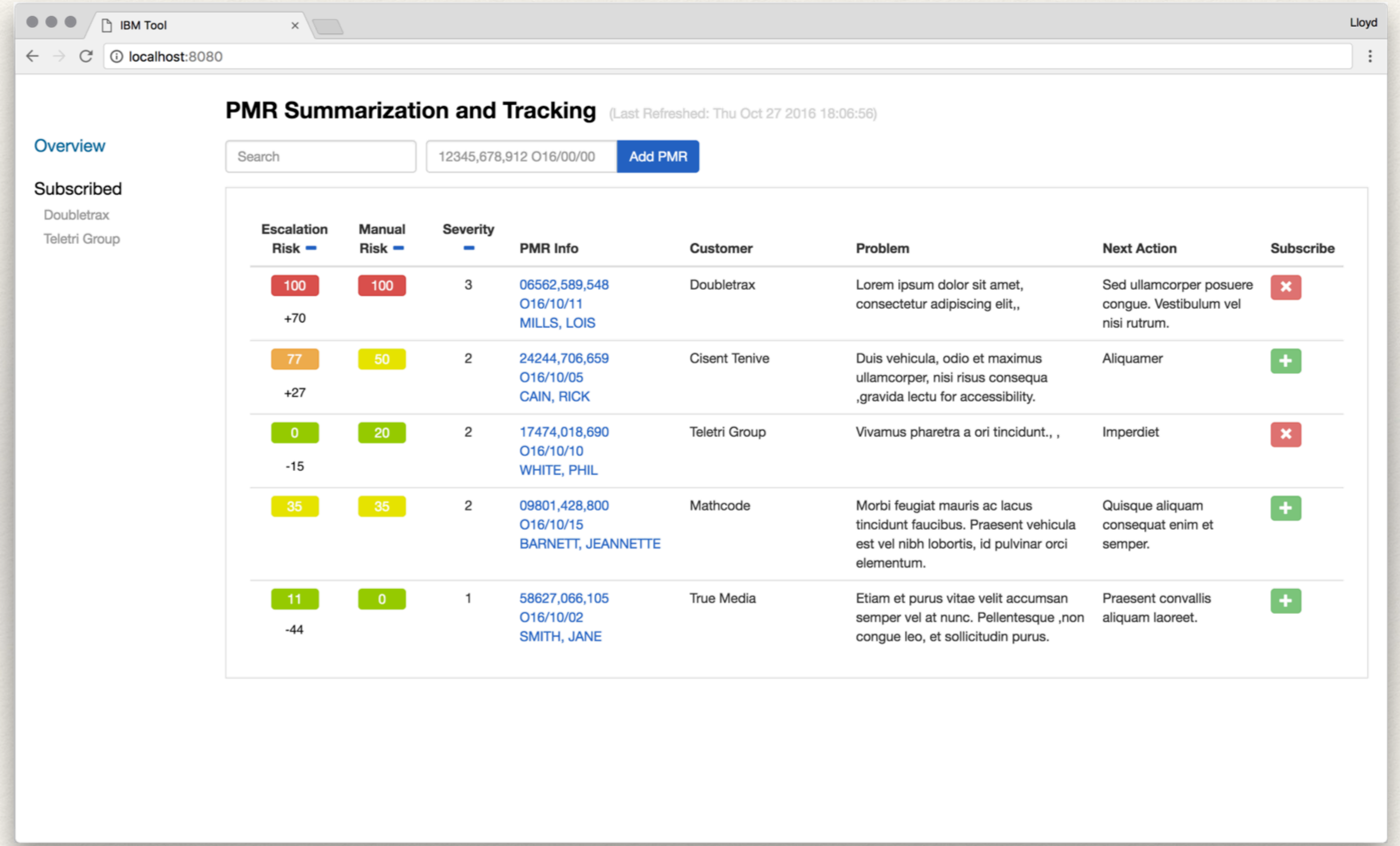
Model Evaluation 1



Model Evaluation 1



Model Evaluation 2: ECrits Tool



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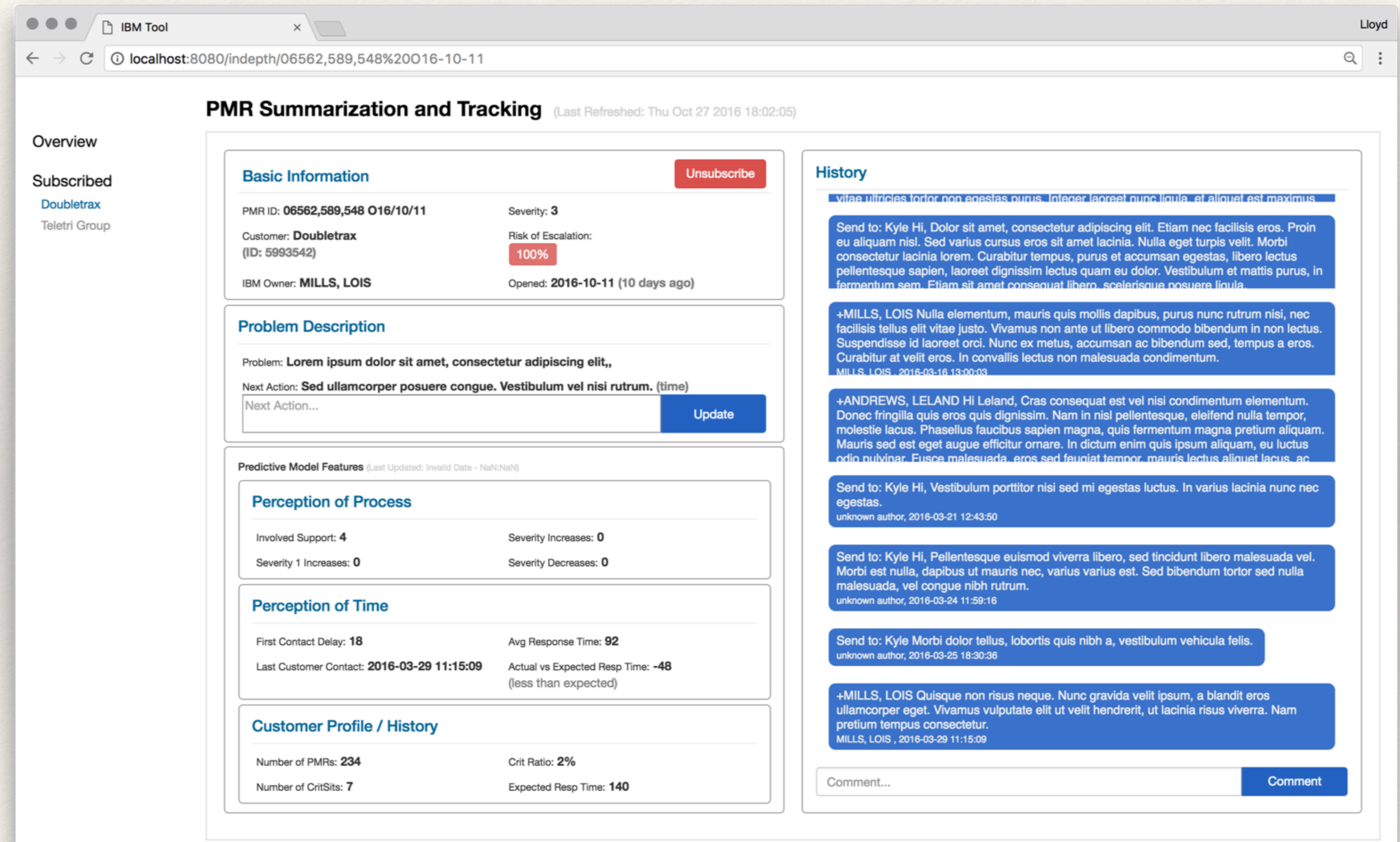


Conclusions

1. Machine Learning can be used to predict escalations against at-risk support tickets

2. Feature Engineering can capture and harness the knowledge of Support Analysts

3. Design Science is a useful methodology when undertaking the complex task of conducting research with industry

Future / In-Progress Work

Addressing the new features to be engineered

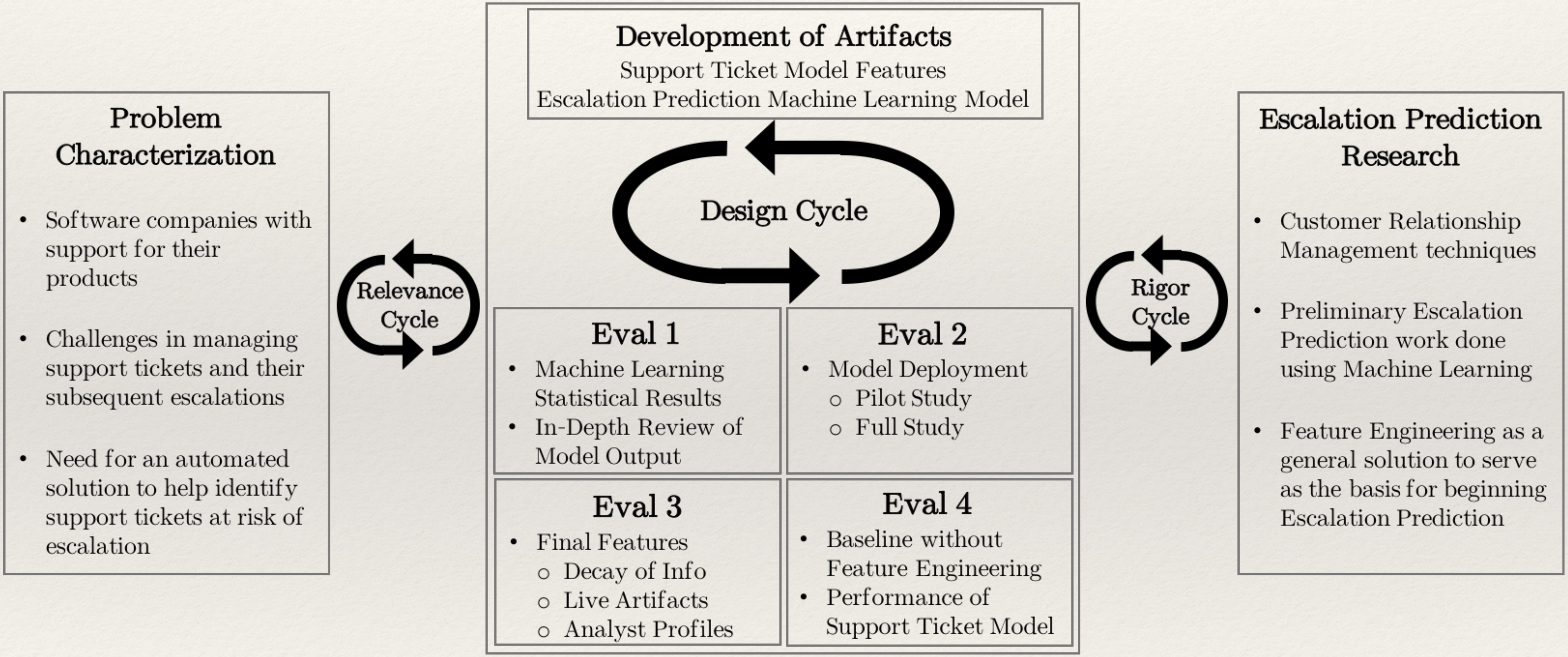
Implementing a Baseline with no feature engineering

Full Implementation with IBM's Ecosystem

Implementing alternate Machine Learning algorithms

Working with support ticket text

Extending the Research



Improved Algorithm

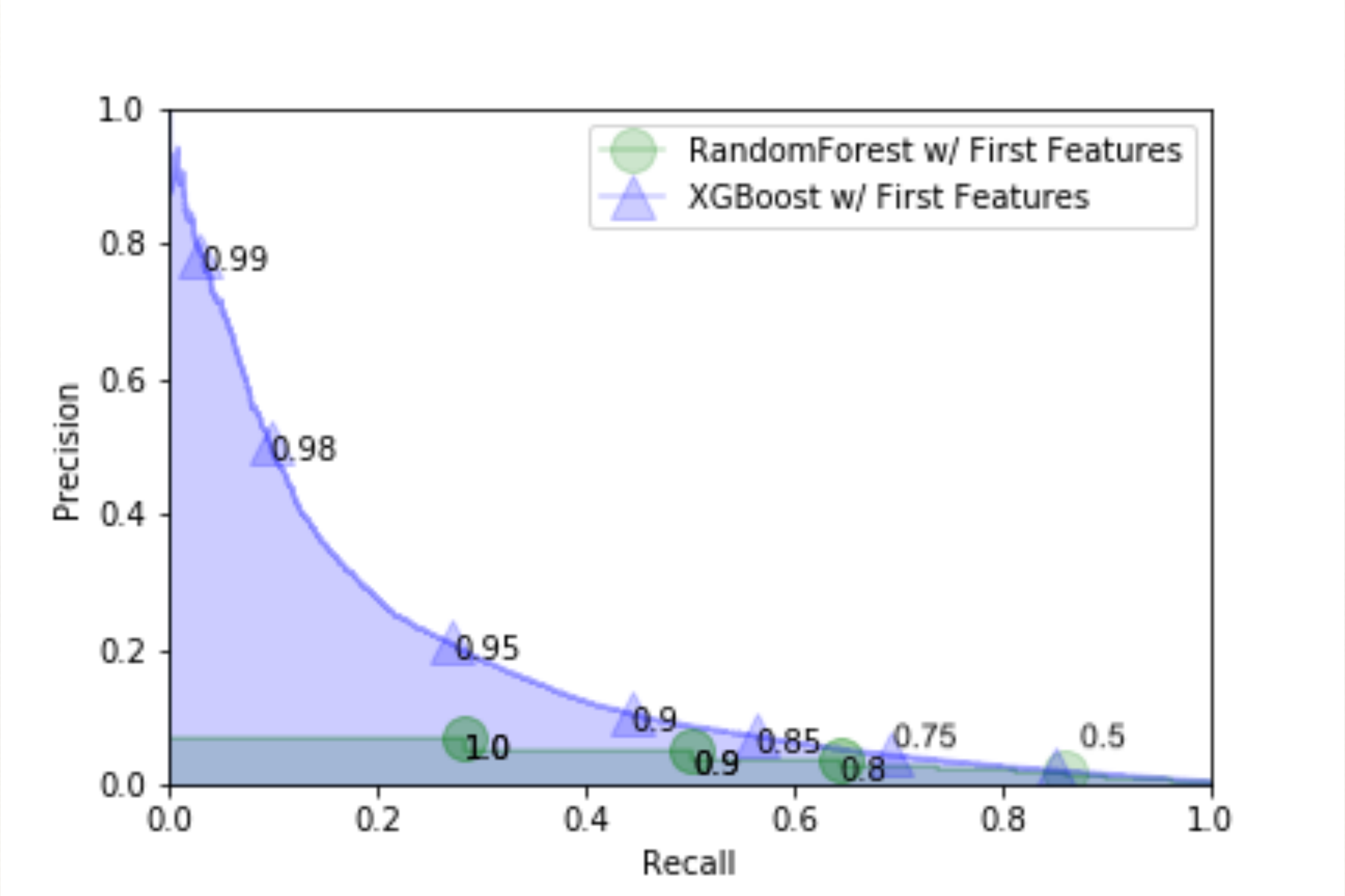
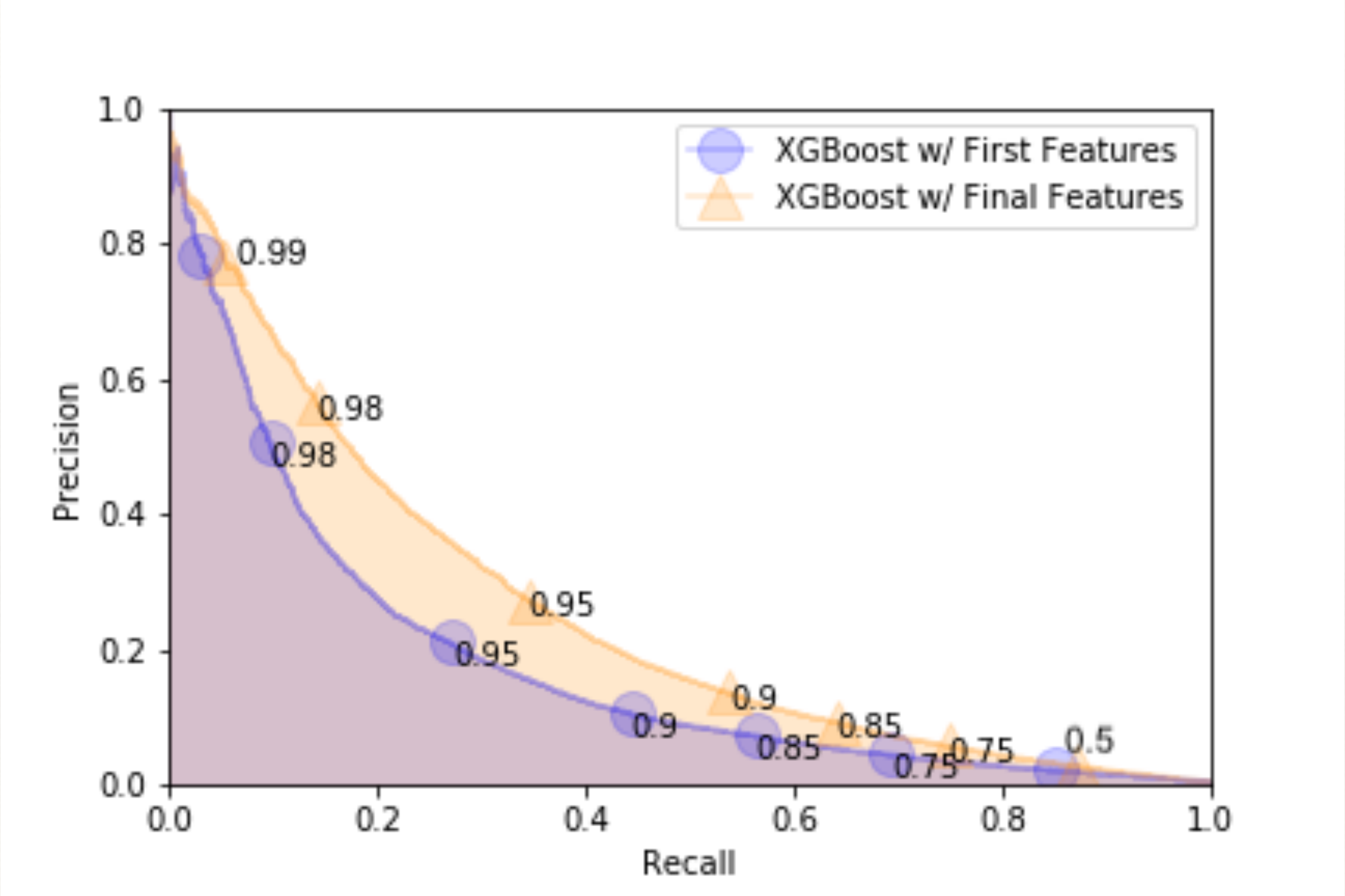


Table 1 Support Ticket Model Features with Stages of Development

Category	Feature	Description	Created or Improved During		
			Problem Characterization	Eval 1	Eval 2
Basic Attributes	Number of entries	Number of events/actions on the PMR	✓		
	Days open	Days from open to close (or CritSit)	✓		
	PMR ownership level	Level of Support (L0 - L3) that is in charge of the PMR, calculated per entry			✓
Customer Perception of Process	Number of support people in contact with customer	Number of support people the customer is communicating with	✓		
	Number of increases in severity	Number of times the Severity increase	✓		
	Number of decreases in severity	Number of times the Severity decrease	✓		
	Number of sev4/sev3/sev2 to sev1 transitions	Number of changes in Severity from 4, 3, or 2, straight to 1	✓		
Customer Perception of Time	Time until first contact	Minutes before the customer hears from IBM for the first time on this PMR	✓		
	Average support response time	Average number of minutes of all the support response times on this PMR	✓		
	Difference in average vs expected response time	(Expectation of support response time) minus (Average support response time)	✓		
	Days since last contact	Number of days since last contact, calculated per entry			✓
	Difference in customer vs analyst expected response time	(Expectation of support response time) minus (Expected analyst response time)			✓
	Decay of Information * Live Artifacts †				
Customer Profile	Number of open PMRs * †	Number of PMRs owned by customer that are open		✓	
	Number of closed PMRs *	Number of PMRs owned by customer that are closed	✓	✓	
	Number of open CritSits * †	Number of CritSits owned by customer that are open		✓	
	Number of closed CritSits *	Number of CritSits owned by customer that are closed	✓	✓	
	Open CritSit to PMR ratio †	(Number of open CritSits) / (Number of open PMRs)		✓	
	Closed CritSit to PMR ratio	(Number of closed CritSits) / (Number of closed PMRs)	✓		
	Expectation of analyst response time	Average of all "Average support response time" of all PMRs owned by a customer	✓		
Support Analyst Profile	Number of open PMRs * †	Number of PMRs owned by customer that are closed			✓
	Number of closed PMRs *	Number of PMRs owned by the analyst that are closed			✓
	Number of open CritSits * †	Number of CritSits owned by the analyst that are open			✓
	Number of closed CritSits *	Number of CritSits owned by the analyst that are closed			✓
	Open CritSit to PMR ratio †	(Number of open CritSits) / (Number of open PMRs)			✓
	Closed CritSit to PMR ratio	(Number of closed CritSits) / (Number of closed PMRs)			✓
	Expected analyst response time	Average of all "Average support response time" of all PMRs owned by an analyst			✓

* in the last N weeks, where N = ∞, 12, 24, 36, and 48

Improved Features



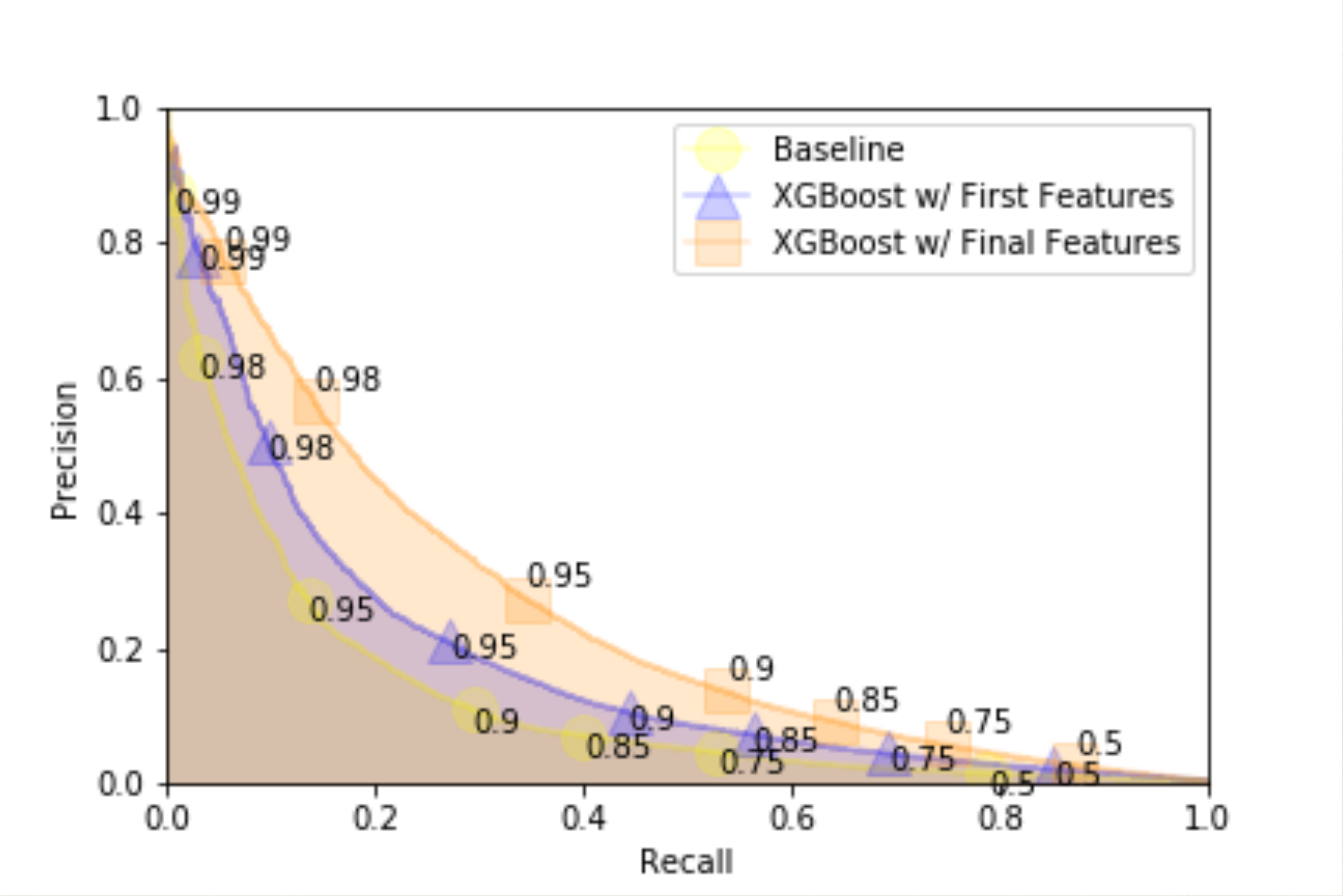
Improved Results

<table>
<tr><th rowspan="2">Actual</th><th rowspan="2">Total</th><th colspan="2">Predicted as</th></tr>
<tr><th>Escalation - No</th><th>Escalation - Yes</th></tr>
<tr><td>Escalation - No</td><td>2,532,745</td><td>2,242,064 (TN)
88.52%</td><td>290,681 (FP)
11.48%</td></tr>
<tr><td>Escalation - Yes</td><td>9,536</td><td>1,205 (FN)
12.64%</td><td>8,331 (TP)
87.36%</td></tr>
</table>

Accuracy	Recall	Precision	Summarization
87.94%	87.36%	2.79%	88.23%

Accuracy	Recall	Precision	Summarization
80.49%	79.94%	1.65%	80.79%

Comparison to Baseline



Research Questions

RQ 1. Are the emotions of customers significantly different during support tickets that escalate versus during support tickets that do not escalate?

RQ 2. Are the trends in the emotions of customers significantly different during support tickets that escalate versus during support tickets that do not escalate?

RQ 3. Can these differences in emotions be utilized to assist support analysts in understanding which customers are likely to escalate their support tickets?

Watson Natural Language Understanding

PMRs Text Entries

- Call summary
- Email exchange
- Manual Annotation

Watson NLU* on Each Entry of a PMR

Output of NLU: **6 Attributes**
- **5 Emotions** (Anger, Disgust, Fear, Joy, Sadness) in [0 – 1]
- **1 Sentiment** in [-1 – 1]

***NLU**: Natural Language Understanding

- For each attribute:

$$\textbf{Tendency}_{\textbf{att}} = \sum \textbf{LocalTendencies}$$
$$\textbf{LocalTendency} = \textbf{Current}_{\textbf{Entry}} - \textbf{Average}_{\textbf{Entries Before Last}}$$

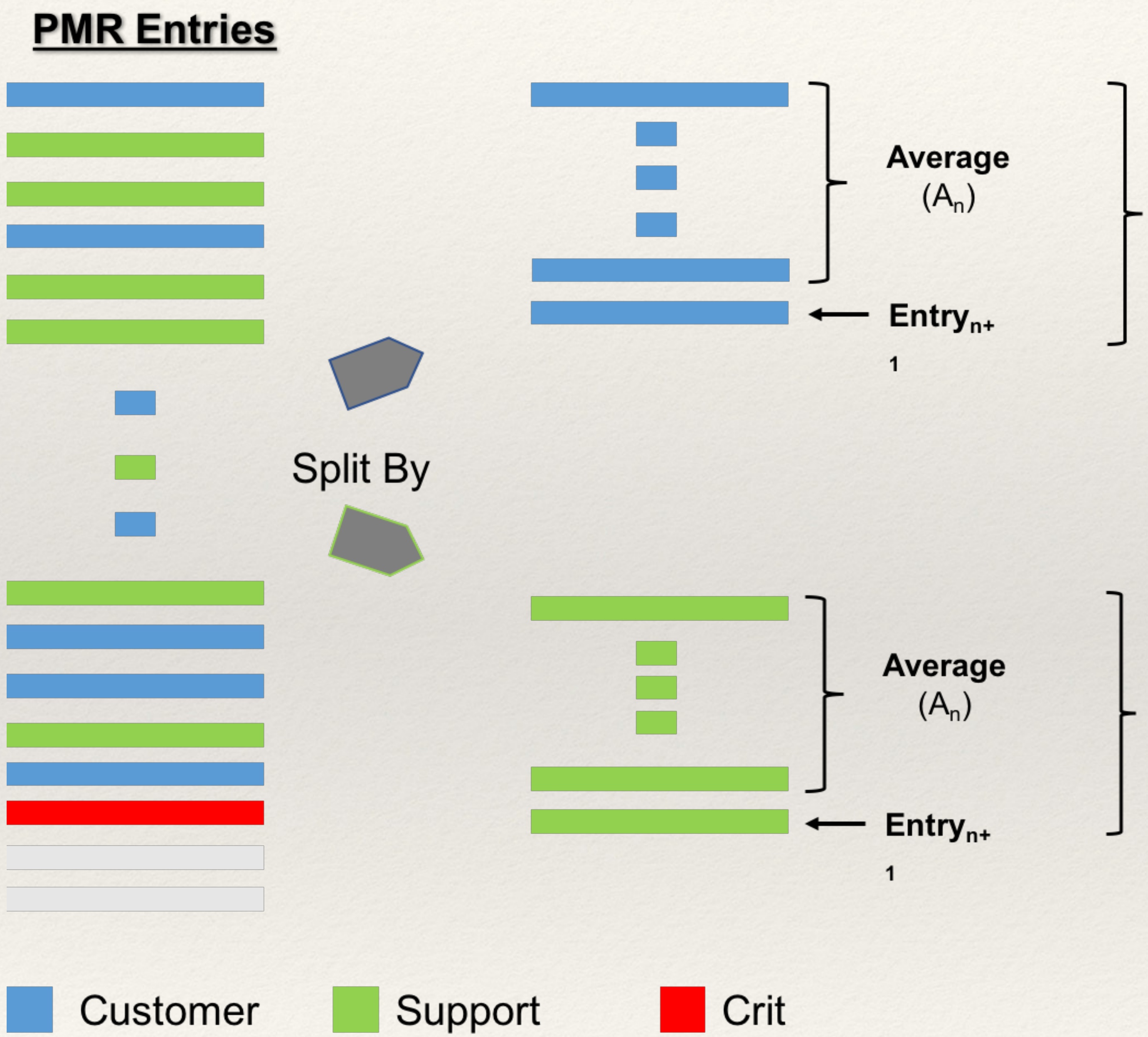
- The Tendency tries to appreciate the PMR global fluctuation/variation trend.

Aggregation of each PMR's Attributes

Clustering on PMRs

K-Means Algorithm

Tendency



LocalTendency = $\text{Entry}_{n+1} - A_n$
On customer entries

LocalTendency = $\text{Entry}_{n+1} - A_n$
On support entries

Difference Testing: NLU Emotions

Customer Crit Analysis						
	# PMRs	# CRs	Avg CRs/PMR			
	208	3253	15.64			
	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Skew	3.21942	5.62226	3.72404	1.59225	0.95461	-0.01712
Kurtosis	15.31188	38.71298	22.66040	1.42776	-0.42217	-0.96636
D'Agostino-Pearson p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Shapiro-Wilk p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Customer NonCrit Analysis						
	# PMRs	# CRs	Avg CRs/PMR			
	94	324	3.45			
	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Skew	3.65583	7.06570	4.30747	1.33707	0.92829	-0.14786
Kurtosis	17.36818	69.35238	25.57274	0.33010	-0.52496	-0.96109
D'Agostino-Pearson p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00098
Shapiro-Wilk p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Customer Crit vs NonCrit	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Mann-Whitney p-value 2-tailed	0.017498009	0.002043608	0.11755407	0.82824515	0.64600566	0.006840317
p <	0.05	0.005				0.01

Difference Testing: NLU Emotions

Support Crit Analysis						
	# PMRs	# CRs	Avg CRs/PMR			
	240	6015	25.06			
	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Skew	3.60804	6.85180	4.24604	1.31043	1.11244	-0.29744
Kurtosis	19.50157	60.04080	31.06732	0.31019	-0.07140	-0.80999
D’Agostino-Pearson p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Shapiro-Wilk p-value	#VALUE!	#VALUE!	#VALUE!	#VALUE!	#VALUE!	#VALUE!

Support NonCrit Analysis						
	# PMRs	# CRs	Avg CRs/PMR			
	113	580	5.13			
	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Skew	3.26043	7.19992	4.10390	1.11259	1.37023	-0.54942
Kurtosis	16.34400	74.23851	27.82842	-0.31806	0.52460	-0.34665
D’Agostino-Pearson p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Shapiro-Wilk p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Support Crit vs NonCrit	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Mann-Whitney p-value 2-tailed	0.39195	0.54057	0.43421	0.85616	0.00369	0.00000
p <					0.005	0.001

Difference Testing: Tendency

Customer Crit Analysis						
	# PMRs	# CRs	Avg CRs/PMR			
	208	3253	15.64			
	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Skew	0.36150	-1.90652	-3.31477	-1.56725	-0.68063	-0.74375
Kurtosis	4.73224	30.05383	27.92736	8.64653	6.13592	7.26335
D'Agostino-Pearson p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Shapiro-Wilk p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Customer NonCrit Analysis						
	# PMRs	# CRs	Avg CRs/PMR			
	94	324	3.45			
	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Skew	-2.39825	-2.35297	-2.98650	-0.26061	-0.41145	0.34563
Kurtosis	15.82966	12.03922	21.48420	0.99622	1.90652	0.89205
D'Agostino-Pearson p-value	0.00000	0.00000	0.00000	0.07476	0.00014	0.07392
Shapiro-Wilk p-value	0.00000	0.00000	0.00000	0.09992	0.00072	0.19200

Customer Crit vs NonCrit	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Mann-Whitney p-value 2-tailed	0.00172	0.09817	0.22529	0.27127	0.79452	0.00149
p <	0.005					0.005

Difference Testing: Tendency

Support Crit Analysis						
	# PMRs	# CRs	Avg CRs/PMR			
	240	6015	25.06			
	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Skew	0.26215	-2.13930	-3.34973	-1.62834	-0.71857	-0.77493
Kurtosis	5.18491	29.62222	29.09388	8.70218	6.81533	7.98232
D'Agostino-Pearson p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Shapiro-Wilk p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Support NonCrit Analysis						
	# PMRs	# CRs	Avg CRs/PMR			
	113	580	5.13			
	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Skew	-2.50322	-2.57349	-3.06617	-0.19679	-0.48804	0.37181
Kurtosis	16.60973	14.69686	23.25213	1.15703	2.52528	1.36107
D'Agostino-Pearson p-value	0.00000	0.00000	0.00000	0.02566	0.00000	0.00278
Shapiro-Wilk p-value	0.00000	0.00000	0.00000	0.06440	0.00002	0.04266

Support Crit vs NonCrit	Anger	Disgust	Fear	Joy	Sadness	Sentiment
Mann-Whitney p-value 2-tailed	0.00039	0.06832	0.27152	0.48716	0.81915	0.00033
	0.001					0.001

Preliminary ML Results

Random Classifier

```
print('Random Classifer')
print('Precision: {0:.2f}%'.format(sum(y) / len(y) * 100))
print('Recall    : 50.00%')
print('Summ.     : 50.00%')
```

```
Random Classifer
Precision: 67.98%
Recall    : 50.00%
Summ.     : 50.00%
```

Gaussian Naive Bayes

```
n_run_m_cv_train_test_output(GaussianNB(), 10, 10, name='GaussianNB')
```

```
GaussianNB: 10-Fold, Avg of 10 Runs
Precision: 81.16% (+/- 13.19)
Recall    : 42.63% (+/- 20.19)
```

Preliminary ML Results

Logistic Regression

```
n_run_m_cv_train_test_output(LogisticRegression(), 10, 10, name='LogisticRe
```

```
LogisticRegression: 10-Fold, Avg of 10 Runs
Precision: 67.94% (+/- 4.62)
Recall    : 95.87% (+/- 14.87)
```

SVM

```
n_run_m_cv_train_test_output(svm.SVC(), 10, 10, name='SVM - SVC')
```

```
SVM - SVC: 10-Fold, Avg of 10 Runs
Precision: 67.99% (+/- 1.53)
Recall    : 100.00% (+/- 0.00)
```

```
n_run_m_cv_train_test_output(svm.NuSVC(), 10, 10, name='SVM - NuSVC')
```

```
SVM - NuSVC: 10-Fold, Avg of 10 Runs
Precision: 69.86% (+/- 11.60)
Recall    : 80.97% (+/- 18.76)
```

```
n_run_m_cv_train_test_output(svm.LinearSVC(), 10, 10, name='SVM - LinearSVC
```

```
SVM - LinearSVC: 10-Fold, Avg of 10 Runs
Precision: 67.72% (+/- 5.26)
Recall    : 95.85% (+/- 16.58)
```

Suggestions?