

Disaster Prediction mit Twitter Daten: Eine kompakte Einführung in die volle Breite der SAS Text Analytics Funktionalitäten

oder "climbing the ROC"

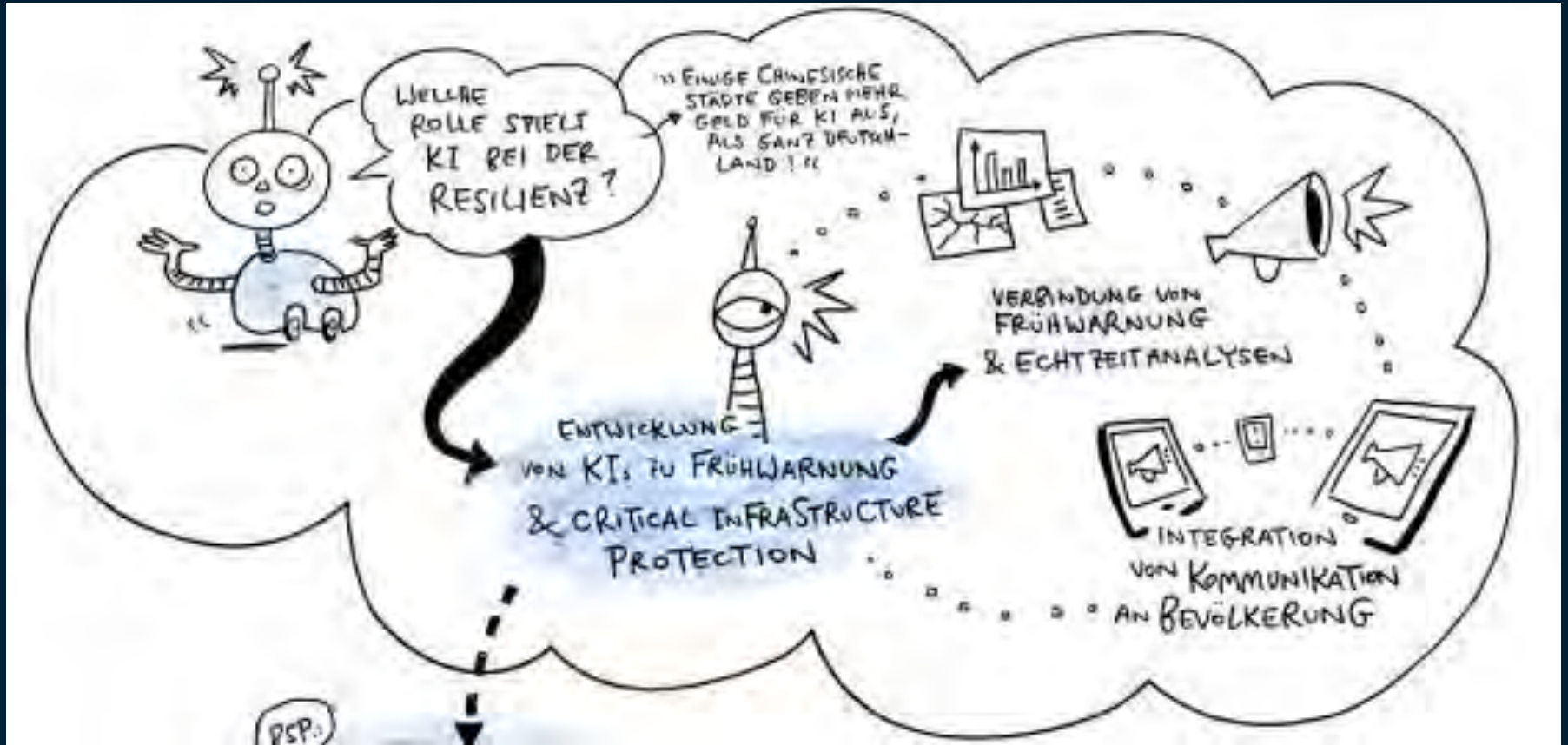
Ulrich Reincke & David Weik, SAS Institute



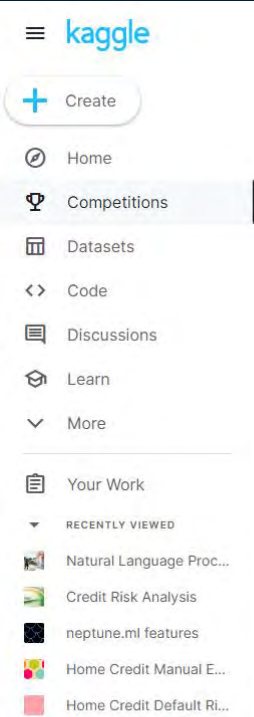
Agenda:

- Anwendungsfall und Datenquelle
- Datenqualität und Daten Management
- Interaktive Visuelle Text Analyse zum Kennenlernen der Daten
- Inkrementelles Verbesserungspotential durch Text Feature Engineering
- Fragen / Diskussion / Links auf weitere Ressourcen

Disaster Management / Resilienz



Datenquelle: Kaggle Competition



The sidebar contains the following items from top to bottom:

- Kaggle logo
- Create button
- Home
- Competitions (highlighted)
- Datasets
- Code
- Discussions
- Learn
- More
- Horizontal separator
- Your Work
- RECENTLY VIEWED
- Natural Language Proc...
- Credit Risk Analysis
- neptune.ml features
- Home Credit Manual E...
- Home Credit Default Ri...



The banner features a search bar at the top. Below it is a competition card for "GettingStarted Prediction Competition" titled "Natural Language Processing with Disaster Tweets". The subtitle reads "Predict which Tweets are about real disasters and which ones are not". It indicates "Kaggle - 736 teams - Ongoing". At the bottom of the card are tabs for Overview, Data (selected), Code, Discussion, Leaderboard, Rules, and Team. On the right side of the card are "My Submissions" and a "Submit Predictions" button.

Dataset Description

What files do I need?

You'll need `train.csv`, `test.csv` and `sample_submission.csv`.

What should I expect the data format to be?

Each sample in the train and test set has the following information:

- The `text` of a tweet
- A `keyword` from that tweet (although this may be blank!)
- The `location` the tweet was sent from (may also be blank)

What am I predicting?

You are predicting whether a given tweet is about a real disaster or not. If so, predict a `1`. If not, predict a `0`.

Files

3 files

Size

1.43 MB

Type

CSV

Twitter Daten der Kaggle Competition

Am Beispiel von Twitter Daten, mit verschiedenen Schlagworten (z. B. Feuer, Flut, Unwetter) zeigen wir, wie Katastrophenereignisse klassifiziert werden können.

Auf einer Stichprobe **manuell klassifizierter Tweets** soll ein Model trainiert werden, das möglichst genau vorhersagt, welche Tweets von echten Katastrophen handeln und welche nicht.



The author explicitly uses the word "ABLAZE" but means it metaphorically. This is clear to a human right away, especially with the visual aid. But it's less clear to a machine.

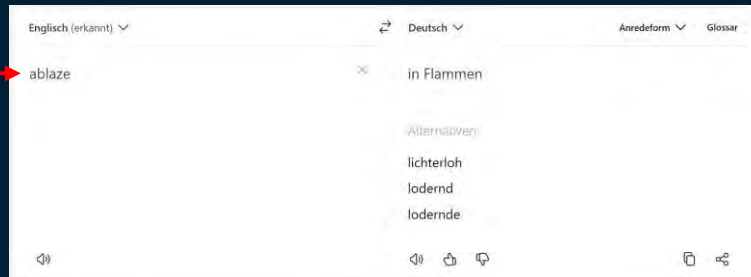
In this competition, you're challenged to build a machine learning model that predicts which Tweets are about real disasters and which one's aren't. You'll have access to a dataset of 10,000 tweets that were hand classified. If this is your first time working on an NLP problem, we've created a [quick tutorial](#) to get you up and running.

Disclaimer: The dataset for this competition contains text that may be considered profane, vulgar, or offensive.

Acknowledgments

This dataset was created by the company figure-eight and originally shared on their '[Data For Everyone](#)' website [here](#).

Tweet source: <https://twitter.com/AnyOtherAnnaK/status/629195955506708480>



Each sample in the train and test set has the following information:

- The `text` of a tweet
- A `keyword` from that tweet (although this may be blank!)
- The `location` the tweet was sent from (may also be blank)

What am I predicting?

You are predicting whether a given tweet is about a real disaster or not. If so, predict a 1. If not, predict a 0.

Kaggle data

train.csv (987.71 kB)



Detail Compact Column

5 of 5 columns ▾

id	keyword	location	text	# target
37			No way...I can't eat that shit	0
38			Was in NYC last week!	0
39			Love my girlfriend	0
40			Cooooo! :)	0
41			Do you like pasta?	0
44			The end!	0
48	ablaze	Birmingham	@bbcmtd Wholesale Markets ablaze http://t.co/1HYXEOHY6C	1
49	ablaze	Est. September 2012 - Bristol	We always try to bring the heavy. #metal #RT http://t.co/YAO1e0xngw	0
50	ablaze	AFRICA	#AFRICANBAZE: Breaking news:Nigeria flag set ablaze in Aba. http://t.co/2nndBGwyEi	1
52	ablaze	Philadelphia, PA	Crying out for more! Set me ablaze	0

test.csv (420.78 kB)

Detail Compact Column

id	keyword	location	text
			hat?
29			Fuck off!
30			No I don't like cold!
35			N000000000! Don't do that!
42			No don't tell me that!
43			What if?!
45			Awesome!
46	ablaze	London	Birmingham Wholesale Market is ablaze BBC News - Fire breaks out at Birmingham's Wholesale Market ht...
47	ablaze	Niall's place SAF 12 SQUAD	@sunkxssedharry will you wear shorts for race ablaze ?
51	ablaze	NIGERIA	#PreviouslyOnDovintv: Toke

Data issues (~400 corrupted lines)

```
6801 8702,sinking,,that horrible sinking feeling when you#TNO#ve been at home on your phone for a while and you realise its been on 3G this whole time,0
6802 8704,sinking,,4 equipment ego break upon dig your family internet hoke excepting versus a sinking term: dfLJEV,1
6803 8705,sinking,,Currency transgress before payday-prison ward sinking-fund payment unsecured loan: jBumZQpK,0
6804 8706,sinking,,?that horrible sinking feeling when you#TNO#ve been at home on your phone for a while and you realise its been on 3G this whole time,0
6805 8708,sinking,,If you're lost and alone or you're sinking like a stone carry onnnn,0
6806 8709,sinking,"Fountain Valley, CA",Lying Clinton sinking! Donald Trump singing: Let's Make America Great Again! https://t.co/zv60cHjclF,0
6807 8710,sinking,Canada,"@AP
6808 Too slow report the sinking boat in the Mediterranean sea what a shame",1
6809 8711,sinking,,We walk the plank of a sinking ship,0
6810 8712,sinking,,The Sinking Ship (@sinkingshipindy): Scarlet Lane Lenore is on replacing Stone Saison (@StoneBrewingCo),0
6811 8714,sinking,,that horrible sinking feeling when you#TNO#ve been at home on your phone for a while and you realise its been on 3G this whole time,0
6812 8715,sinking,,In the movie 'Titanic' Jack and Rose both could have stayed on the wooden beam without it sinking.,0
6813 8717,sinking,"Michigan, USA",#TNO#If your lost & alone or your sinking like a stone carry on&á;0
6814 8718,sinking,,If there's a chance will get a gander of the sinking ship that is #TNA too. Can't help but appease my morbid curiosity. #DestinationIMPAC
6815 8720,sinking,"Sacramento, CA",So happy to be exercised of the demon of @ATT. Price kept rising service kept sinking. #goodbye,0
6816 8721,sinking,Liverpool,Do you feel like you are sinking in low self-image? Take the quiz: http://t.co/bJoJVM0piX http://t.co/wHOC7LHb5F,1
6817 8722,sinking,Haarlem,INVESTMENT NEWS Keurig Green Mountain Inc. Third-Quarter Earnings: Shares Sinking After-Hours - Stocks in the New#TNO#_ http://t.co
6818 8723,sinking,@WCCORosen did Lloyds of London insure your bet with @CoryCove #sinking #twins,0
6819 8724,sinking,Queensland,Sinking the Slipper or Putting the Boot In http://t.co/blbx0ERuep,0
6820 8726,sinking,HOMRA.,"In your eyes I see the hope
6821 I once knew.
6822 I'm sinking.
6823 I'm sinking
6824 away from you.
6825 Don't turn around
6826 you'll see...|
6827
6828 You can make it.",0
6829 8727,sinking,,That horrible sinking feeling when you#TNO#ve been at home on your phone for a while and you realise its been on 3G this whole time.,0
6830 8728,sinking,"Ciudad Auti noma de Buenos Aires, Argentina",'I'm sinking down in the darkest dream so deep so cold this pain inside of me my love for yc
6831 8729,sinking,,Sinking carb consultative assembly plans could subconscious self live straight a leading way of escape: XkDrx,0
6832 8732,sinking,"Not where I want to be, yet",This is Lara she likes sinking her teeth into my flesh and clawing my arms ?????? http://t.co/J43NWkX0X3,0
6833 8733,sinking,London,Spent too many hours sinking into the wonderfully created worlds of Mafia and Mafia II in my life. Excited for another installment.
6834 8734,sinking,"Duval, WV 25573, USA ?",Do you feel like you are sinking in unhappiness? Take the quiz: http://t.co/BTjPEO0Bto http://t.co/ClyJ32L333,0
6835 8735,sinking,,That horrible sinking feeling when you#TNO#ve been at home on your phone for a while and you realise its been on 3G this whole time,1
```

Repaired SAS data tables

New Options View Open Save All SAS Studio compute context

Start Page anonymize.sas SWEE.SWEE_NLP_DISASTER_TRAIN x +

SWEE_NLP_DISASTER_TRAIN Table rows: 7613 Columns: 6 of 6 Rows 1 to 200 (filtered) | id>8500

	id	keyword	location	text	target	Unique_ID
144	8702	sinking		that horrible sinking feeling when you've been at home on your phone for a while and you realise its been on 3G this whole time	0	423145
145	8704	sinking		4 equipment ego break upon dig your family internet hoke excepting versus a sinking term: dfLJEV	1	424145
146	8705	sinking		Currency transgress before payday-prison ward sinking-fund payment unsecured loan: jBUmZQpK	0	425145
147	8706	sinking		?that horrible sinking feeling when you've been at home on your phone for a while and you realise its been on 3G this whole time	0	426145
148	8708	sinking		If you're lost and alone or you're sinking like a stone carry onnnn	0	427145
149	8709	sinking	Fountain Valley, CA	Lying Clinton sinking! Donald Trump singing: Let's Make America Great Again! https://t.co/zv60ChjclF	0	428145
150	8710	sinking	Canada	@AP Too slow report the sinking boat in the Mediterranean sea what a shame	1	429145
151	8711	sinking		We walk the plank of a sinking ship	0	430145
152	8712	sinking		The Sinking Ship (@sinkingshipindy): Scarlet Lane Lenore is on replacing Stone Saison (@StoneBrewingCo)	0	431145
153	8714	sinking		that horrible sinking feeling when you've been at home on your phone for a while and you realise its been on 3G this whole time	0	432145
154	8715	sinking		In the movie 'Titanic' Jack and Rose both could have stayed on the wooden beam without it sinking.	0	433145
155	8717	sinking	Michigan, USA	if you lost & alone or your sinking like a stone carry on&aj	0	434145
156	8718	sinking		If there's a chance will get a gander of the sinking ship that is #TNA too. Can't help but appease my morbid curiosity. #DestinationIMPACT	0	435145
157	8720	sinking	Sacramento, CA	So happy to be exercised of the demon of @ATT. Price kept rising service kept sinking. #goodbye	0	436145
158	8721	sinking	Liverpool	Do you feel like you are sinking in low self-image? Take the quiz: http://t.co/bJoJVM0pjX http://t.co/wHOC7LHb5F	1	437145
159	8722	sinking	Haarlem	INVESTMENT NEWS Keurig Green Mountain Inc. Third-Quarter Earnings: Shares Sinking After-Hours - Stocks in the New http://t.co/GtdNW1SpVi	0	438145
160	8723	sinking		@WCCORosen did Lloyds of London insure your bet with @CoryCove #sinking #twins	0	439145
161	8724	sinking	Queensland	Sinking the Slipper or Putting the Boot In http://t.co/b1bx0ERuep	0	440145
162	8726	sinking	HOMRA.	In your eyes I see the hope I once knew. I'm sinking. I'm sinking away from you. Don't turn around you'll see... You can make it.	0	441145
163	8727	sinking		That horrible sinking feeling when you've been at home on your phone for a while and you realise its been on 3G this whole time.	0	442145

Repair Code

Run Cancel Undo Copy to My Snippets Code to Flow Debug Clear Log Oct 13, 2022, 3:40:57 PM

```
Code
1 libname kaggle '/greenmonthly-export/ssemnthly/homes/Rens.Feenstra@sas.com/Giti
2 filename kaggle '/greenmonthly-export/ssemnthly/homes/Rens.Feenstra@sas.com/Gi
3
4 data train;
5 infile kaggle dlm=', ' firstobs=2 dsd length=lengthe;
6 length line line2 $ 512 id 8 keyword $ 25 word location $ 75 text $ 256 tar
7 input line2 $varying. lengthe;
8 if lengthe=0 then return;
9 word=scan(line2,1,',');
10 id=input(word,5.);
11 if id=. then do;
12     line=catx(' ',line,line2);
13     word=scan(line,1,',');
14     id=input(word,5.);
15     counter+1;
16 end;
17 else do;
18     line=line2;
19     counter=0;
20 end;
21 retain id counter 0 line;
22
23 run;
24 data train;
25 set train end=last;
26 if id=lag(id) then prev=1; else prev=0;
27 if id=lag2(id) then prev=2;
28 if id=lag3(id) then prev=3;
29 if id=lag4(id) then prev=4;
30 if id=lag5(id) then prev=5;
31 if id=lag6(id) then prev=6;
32 if id=lag7(id) then prev=7;
33 if id=lag8(id) then prev=8;
34 if id=lag9(id) then prev=9;
35 if id=lag10(id) then prev=10;
36 if id=lag11(id) then prev=11;
37 if id=lag12(id) then prev=12;
38 if id=lag13(id) then prev=13;
39 if prev>max then max=prev;
40 if last then put max=;
41 retain max 0;
42 run;
```

Log Output Data (2)

Errors (0) Warnings (1) Notes (53)

WARNING: Limit set by ERRORS= option reached. Further errors of this type will not be printed.

Access Permission=rw-r--r--,
Last Modified=13Oct2022:15:40:57
NOTE: 7613 records were written to the file KAGGLE2.
The minimum record length was 15.
The maximum record length was 203.
NOTE: There were 8561 observations read from the data set WORK.TRAIN.
NOTE: The data set WORK.TRAIN has 7613 observations and 11 variables.
NOTE: DATA statement used (Total process time):
real time 0.02 seconds
cpu time 0.03 seconds

132
133 data casuser.train;
134 infile kaggle2 dlm=', ' dsd length=lengthe;
135 length id 8 keyword \$ 25 location \$ 75 text \$ 256 target 8;
136 input id keyword location text target;
137 run;
NOTE: The infile KAGGLE2 is:

Filename=/opt/sas/viya/config/var/tmp/compsrv/default/0d65cabe-f684-4a27-9a
1bb3c7e-8a7f-452e-a315-658317484180-d5mqv/#LN00137,
Owner Name=UNKNOWN,Group Name=UNKNOWN,
Access Permission=rw-r--r--,
Last Modified=13Oct2022:15:40:57,
File Size (bytes)=987240
NOTE: 7613 records were read from the infile KAGGLE2.
The minimum record length was 15.
The maximum record length was 203.
NOTE: The data set CASUSER.TRAIN has 7613 observations and 5 variables.
NOTE: DATA statement used (Total process time):
real time 0.16 seconds
cpu time 0.07 seconds

Minimum Work

Model Comparison

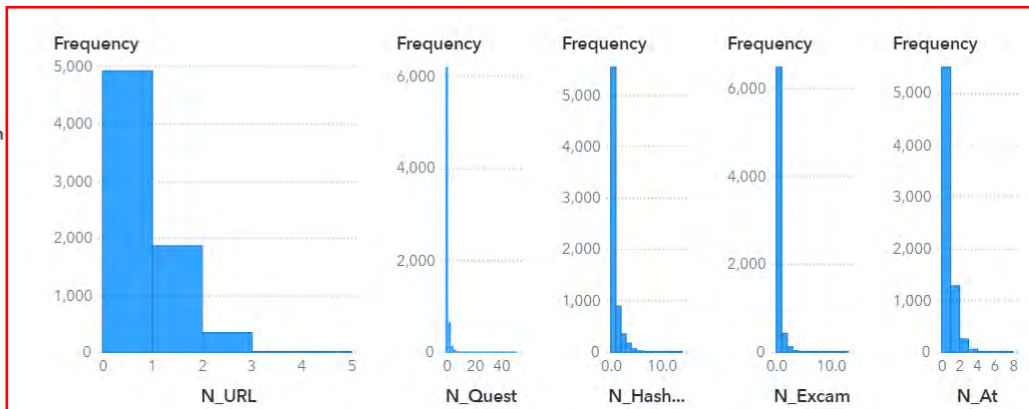
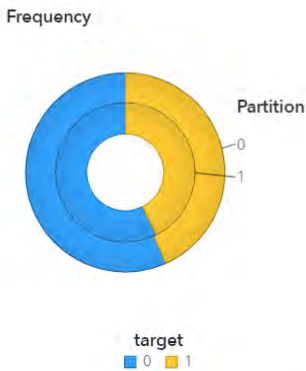
Champi...	Name	KS (Youden)	Accuracy	Area Under ROC	Cumulative Lift	Cumulative Captured Response Percentage	Cutoff	Data Role
	SVM	0.4651	0.7248	0.8021	2.0461	20.4614	0.5000	VALIDATE
	Forest	0.4599	0.7274	0.8062	2.1765	21.7653	0.5000	VALIDATE
	Bayesian Network	0.4464	0.7375	0.7902	2.1665	21.6650	0.5000	VALIDATE
	Logistic Regression	0.1201	0.5911	0.5560	1.6696	16.6962	0.5000	VALIDATE

_ulr_nlp_Disaster_Prediction_Tweets_VTA

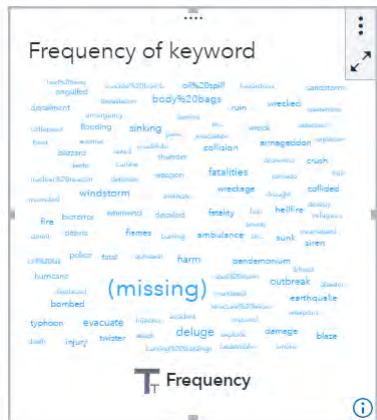
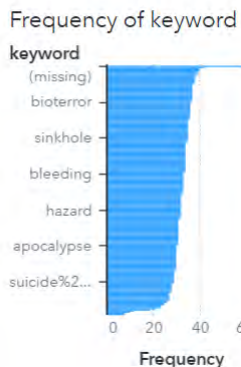
Editing

Page 8 Page 1 Page 2 Page 3 Page 4 Page 5 Page 6 Page 9 +

Filters: No selections



Location	Frequency
-?s?s??s-	~5,000
?	~1,000
? icon by @Ha...	~500
? Jet Life ?	~500
? miranda ? 5...	~500
? Philly Baby ?	~500
??	~500
?? ??	~500
?? ?+254? ? \...	~500
?? Cloud Mafi...	~500
???	~500



id	keyword	Location	Partition	target	Text
74	ablaze	England.	0	0	First night with retainers in. It's quite weird. Better get used to
75	ablaze	Barbados	1	0	SANTA CRUZ À%À,Ã" Head of the St Elizabeth Police Superi
76	ablaze	Abuja	0	0	Noches El-Bestia @Alexis_Sanchez: happy to see my teamm
77	ablaze	Sao Paulo, Brazil	0	0	Set our hearts ablaze and every city was a gift And every skyli
78	ablaze	hollywoodland	1	0	They sky was ablaze tonight in Los Angeles. I'm expecting IG
79	ablaze		1	0	Revel in yours wmv videos by means of mac farewell ablaze v
80	ablaze	Twitter Lockout in progress	1	0	Rene Ablaze & Jacinta - Secret 2k13 (Fallen Skies Edit) -
81	ablaze	Calgary, AB	1	0	#NowPlaying: Rene Ablaze & Ian Buff - Magnitude http:
82	ablaze	San Francisco	0	0	@ablaze what time does your talk go until? I don't know if I ca
83	ablaze	Birmingham	1	1	@bbcmtd Wholesale Markets ablaze http://t.co/IHYXEOHY6i
84	ablaze	AFRICA	0	1	#AFRICANBAZE: Breaking news:Nigeria flag set ablaze in Ab

Editing

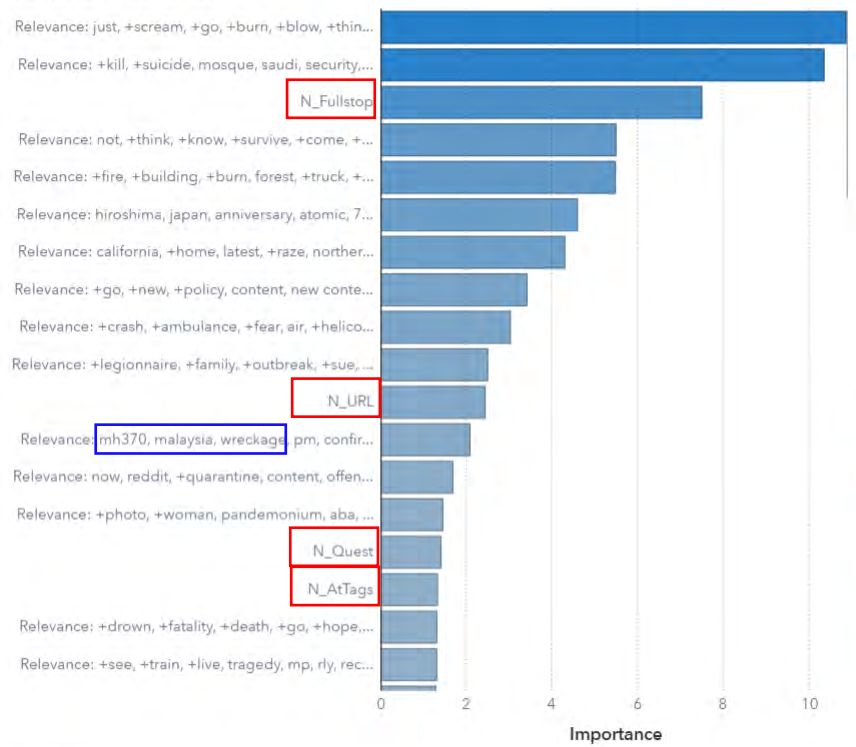
_ulr_nlp_Disaster_Prediction_Tweets_VTA

🔄 🏠 📄 ⋮ 1

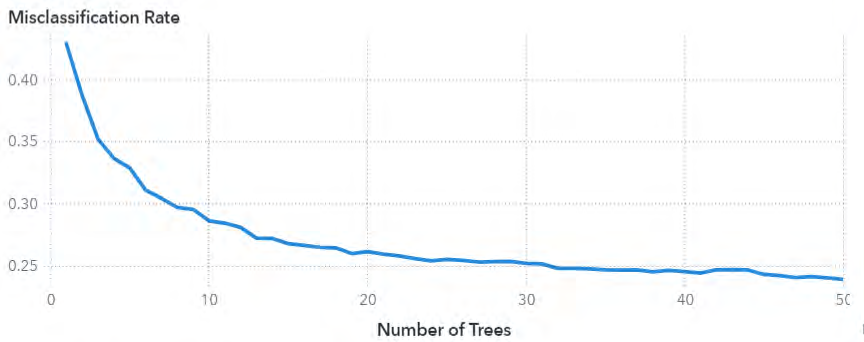
Page 8 Page 1 Page 2 Page 3 Page 4 Page 5 Page 6 Page 9 Page 10 ⋮ +

Gradient Boosting target Event: 1 ▾ Fit: KS (Youden) 0.5039 ▾ Observations: 7,176 of 7,176 Create Pipeline

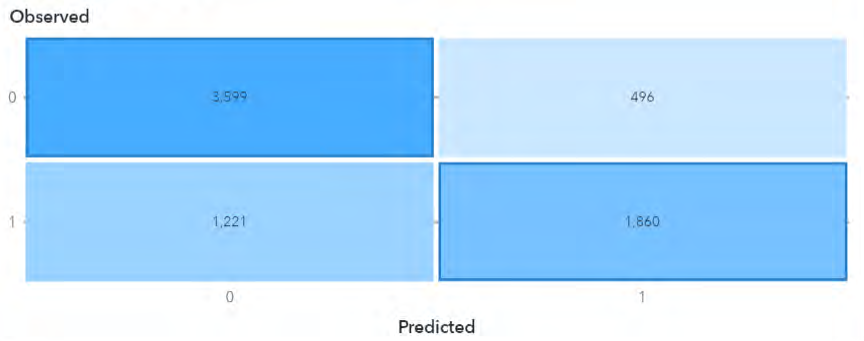
Variable Importance



Iteration Plot



Confusion Matrix





Search or jump to...

Pull requests Issues Marketplace Explore



snref / SWEE_NLP_disaster Private

Unwatch 2 Fork 0 Star 1

Code Issues Pull requests Actions Projects Security Insights Settings

main 1 branch 0 tags

Go to file Add file Code

About

File Name	Description	Time Ago
snref latest and greatest		0ed8142 25 days ago 55 commits
Create_dataset_for_VDMML.sas	new changes	27 days ago
Custom-Step-Dev-File.sas	Implement Bool Rule Feature	27 days ago
Extract Text Features.step	Implement Bool Rule Feature	27 days ago
Get-Link-Features-Just-Python.py	Add additional content for scraping link data	2 months ago
Get-Link-Features.py	Add additional content for scraping link data	2 months ago
Loading-Data-Feature-Extraction.flw	Implement Bool Rule Feature	27 days ago
Loading-Data-Feature-Extraction_snfr...	small updates	25 days ago
Partitioning.ctl	new tweet text extraction step	2 months ago
README.md	Update README.md	2 months ago
Read_train_csv.sas	latest and greatest	25 days ago
RollingRegexQueryFromText_001.sas	Add Custom RegEx feature by Ulrich	2 months ago
Run_tmينة_actionset.sas	new tweet text extraction step	2 months ago
TM-Milena.ipynb	Update TM-Milena.ipynb	2 months ago
To-Dos-Custom-Step.md	Implement Bool Rule Feature	27 days ago
_ETM_DISTINCT_LINKS.csv	Add additional content for scraping link data	2 months ago
_URL_TA_BoolRule_Desaster_tweet_0...	BooleRuleFeatureExtraction	2 months ago
_ulr_swee_nlp_desaster_Prediction_tw...	Create_ulr_swee_nlp_desaster_Prediction_tweets_002.sas	2 months ago
_ulr_tweets_desaster_pred_kaggle.sas...	latest and greatest	25 days ago
boolRule-Dev-For-CS.sas	Implement Bool Rule Feature	27 days ago
comparing_models.docx	latest and greatest	25 days ago

Kaggle Disaster competition

- Readme
- 1 star
- 2 watching
- 0 forks

Releases

No releases published
[Create a new release](#)

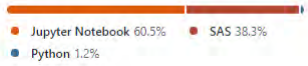
Packages

No packages published
[Publish your first package](#)

Contributors 4

- Criptic David Weik
- snref Rens Feenstra
- MilenaStepien93
- SnowTiger13

Languages

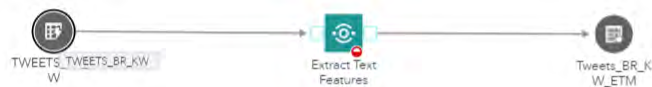


- Libraries
- Connected Libraries
 - MAPS
 - MAPSGFK
 - MAPSSAS
 - PUBLIC
 - SASDATA
 - SASHELP
 - SASUSER
 - TMPCAS
 - _ULR_TWEETS_DESASTE
 - _ULR_TWEETS_DESASTE
 - TWEETS_BR_KW
 - WORK

Start Page *_ulr_sweet_nlp_disaster_prediction_tweets_007.sas *Flow.flw

Run Cancel Add View

Flow Generated Code Submission



TWEETS_BR_KW

Table Properties Published Columns Preview Data Node Notes

Library: *

TMPCAS

Table name: *

TWEETS_BR_KW

> Properties

Submission Order

You can specify the order in which swimlanes are run. ⌵

Enable submission order

Libraries

- Connected Libraries
 - MAPS
 - MAPSGFK
 - MAPSSAS
 - PUBLIC
 - SASDATA
 - SASHELP
 - SASUSER
 - TMPCAS
 - _ULR_TWEETS_DESASTE
 - _ULR_TWEETS_DESASTE
 - TWEETS_BR_KW
 - WORK

Start Page * _ulr_swee_nlp_desaster_prediction_tweets_007.sas * Flow.flw x

Run Cancel Add View

Flow Generated Code Submission



Tweets_BR_KW_ETM

No columns were found. The table defined in the Table Properties may not exist yet.

Table Properties Options Published Columns Preview Data Node Notes

Library: *

work

Table name: *

Tweets_BR_KW_ETM

Properties

Label:

Columns

--

Date created:
(not available)

Date modified:
(not available)

Encoding:
(not available)

Rows

--

Submission Order

You can specify the order in which swimlanes are run. 0

Enable submission order



Submission Order

You can specify the order in which swimlanes are run.

Extract Text Features

Base Metadata Custom RegEx Pattern Link Data Text Analytics - Start Text Analytics - Topic Creation Text Analytics - Bool Rule Creation **Information** Node Notes

All variables created in addition start with _etm.

This step only works with SAS Base Engine tables.

Select the column that contains the Text: *

text

Do you want to create a percentage of the used available characters?

How many characters are allowed?

240

For the Extraction of User Mentions, Hashtags and Links there is four stages that build on top of each other:

1. A count per Text of the Feature
2. A concatenated Column of the Feature per Text
3. A separate column for each Feature per Text (this is non-unique, there will be n columns created depending on the most Features found in one Text)
4. Create Co-Occurrence column for the top Features

You need to accept the concatenated columns in order to get the ability to have the concatenated values seperated in their own columns and to create Co-Occurrences.

Extract User Mentions

- Do you want to extract a Count of **User Mentions (@)?**
- Do you want to create a concatenated Column of all User Mentions per Text?
- Do you want to create separated columns for User Mentions?
- Do you want to create Co-Occurrences for User Mentions?

Times a User has to be mentioned to be counted as a significant Co-Occurrence

5

Limit the number of Co-Occurrences for User Mentions to the Top (highly suggested to reduce dataset size):

25

Extract Hashtags

- Do you want to extract a **Count of Hashtags (#)?**
- Do you want to create a concatenated Column of all Hashtags per Text?
- Do you want to create separated columns for Hashtags?
- Do you want to create Co-Occurrences for Hashtags?

Times a Hashtags has to be mentioned to be counted as a significant Co-Occurrence

10

Limit the number of Co-Occurrences for Hashtags to the Top (highly suggested to reduce dataset size):

30

Extract Links

Please note that for the Link Data page options to unlock you have to create a concatenated column and separated columns for the links here.

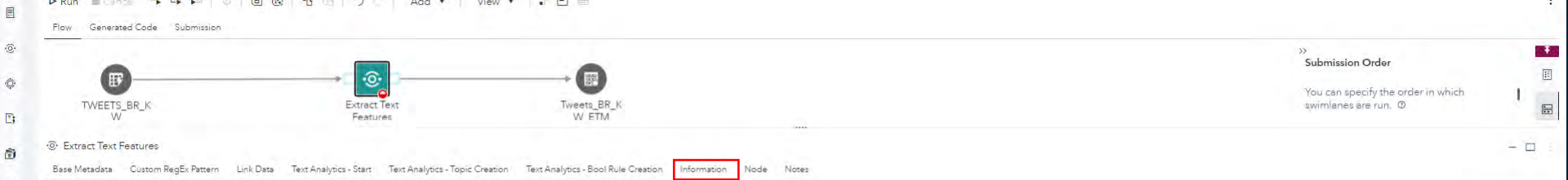
- Do you want to extract a **Count of Links (http)?**
- Do you want to create a concatenated Column of all Links per Text?
- Do you want to create separated columns for Links?
- Do you want to create Co-Occurrences for Links?

Times a Links has to be mentioned to be counted as a significant Co-Occurrence

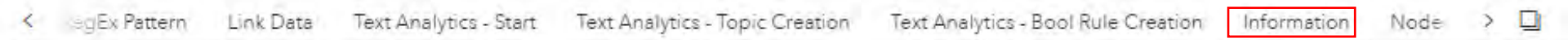
5

Limit the number of Co-Occurrences for Links Mentions to the Top (highly suggested to reduce dataset size):

25



Extract Text Features



The output always contains the following for each Text:

- Number of Full Stops
- Number of Questions Marks
- Number of Exclamation Points
- Number of User Mentions
- Number of Hashtags
- Number of Links
- Total Word Count
- Total Character Count

If you use the of the Additional Metadata or Text Analytics features a unique ID is generated for your text called `_etm_ID`

This custom step was created in collaboration between:

- David.Weik@sas.com
- Ulrich.Reincke@sas.com
- Rens.Feenstra@sas.com



Submission Order

You can specify the order in which swimlanes are run. ⓘ

Extract Text Features

Base Metadata **Custom RegEx Pattern** Link Data Text Analytics - Start Text Analytics - Topic Creation Text Analytics - Bool Rule Creation Information Node Notes

Please enter a valid RegEx pattern here - you have to enclose it in / and you can specify a RegEx Flag.*

Only create a Feature if the Pattern occurs n times:

Add Tables summarizing the findings to the Results

Snippet Context Window for the Pattern (Optional)

Enables you to create an additional output table that contains next to the extracted pattern some surrounding text to better enable you to judge if your pattern worked as you intended.

To enter a custom name for this table please right click the step in the flow > Expand Output Ports and then connect your desired output table to the new port.

Do you want to create an additional table containing some context around the found RegEx Pattern?

Number of characters extracted before and after the Occurrence:

Feature Association with Target (Optional)

If you have a numerical binary target variable with values 0 and 1 then you can create additional statistics to show the association of the target level with the feature.

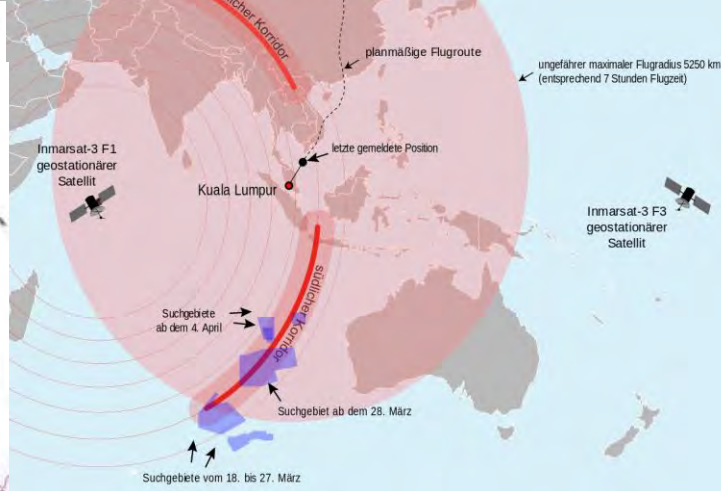
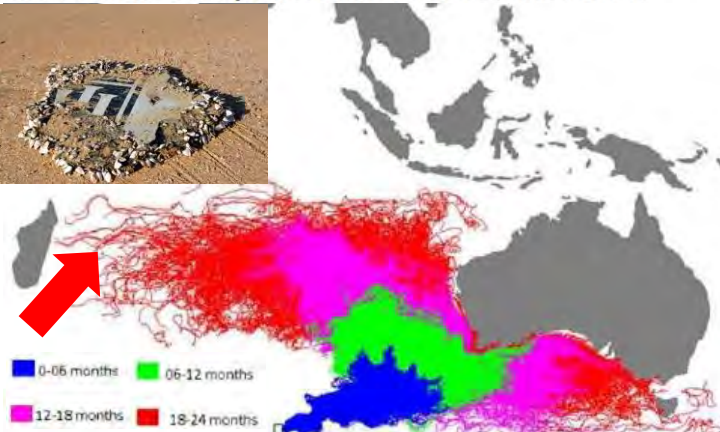
Do you have a binary numeric Target variable?

Please select the Target variable from the Input D...*

Minimum Target Mean:

Maximum Target Mean

An incredible oceanographic model predicted a year ago that MH370 would end up where debris has now been found



Malaysia Airlines Flight 370



The missing aircraft, 9M-MRO, taking off from Paris in 2011

Disappearance	
Date	8 March 2014; 8 years, 5 months ago
Summary	Inconclusive, some debris found
Site	Southern Indian Ocean (presumed)

Aircraft	
Aircraft type	Boeing 777-200ER
Operator	Malaysia Airlines
IATA flight No.	MH370
ICAO flight No.	MAS370
Call sign	Malaysian 370
Registration	9M-MRO
Flight origin	Kuala Lumpur International Airport
Destination	Beijing Capital International Airport
Occupants	239
Passengers	227
Crew	12
Fatalities	239 (presumed)
Survivors	0 (presumed)

Malaysia Airlines Flight 370

- Search (JACC) - Timeline
- Satellite communications analysis
- Disappearance theories

See also: [List of missing aircraft](#)

Looking for Airline Flight Codes e.g. „mh370“ in the twitter data:

Target Association

Target_Mean	Doc_CNT	NPos	NNeg	Occurance	Text Snippets: Detected Occurance Instance Examples in Text
Lowcase					
100.00%	51	53	0	mh370	o be from MH370 - Nation erving: MH370: Aircraft to flight MH370 Ä%Ä,Ä' Ma rmed from MH370; relative om Flig
88.89%	9	8	1	utc2015	01:04:01 UTC2015-08-05 15: 01:04:01 UTC2015-08-05 15: 01:04:01 UTC2015-08-05 15: 01:04:01 UTC2015-08-05 15:
Propcase					
100.00%	51	52	0	MH370	o be from MH370 - Nation erving: MH370: Aircraft to flight MH370 Ä%Ä,Ä' Ma rmed from MH370; relative om Flig
88.89%	9	8	1	UTC2015	01:04:01 UTC2015-08-05 15: 01:04:01 UTC2015-08-05 15: 01:04:01 UTC2015-08-05 15: 01:04:01 UTC2015-08-05 15:

Parameter Settings: Maximum Target Mean=2, Maximum Target Mean=8, Minimum Document Frequency=10

REGULAR EXPRESSION

regex101.com

no match

:/ |insert your regular expression here /

TEST STRING

I'll fly with mh12 or BA123 or af1234 or EK 77 or
klm 87 or lh 1230 or maybe I go by foot.

REGULAR EXPRESSION

regex101.com

1 match (26 steps, 0.0ms)

```
[a-z]{2,3}\s{0,1}\d{2,4}\b
```

TEST STRING

I'll fly with mh12 or BA123 or af1234 or EK 77 or klm 87 or lh 1230 or maybe I go by foot.

EXPLANATION

`[a-z]{2,3}\s{0,1}\d{2,4}\b`

- Match a single character present in the list below** `[a-z]`
 - `{2,3}` matches the previous token between 2 and 3 times, as many times as possible, giving back as needed (greedy)
 - `a-z` matches a single character in the range between a (index 97) and z (index 122) (case sensitive)
- `\s` matches any whitespace character (equivalent to `[\r\n\t\f\v·]`)
 - `{0,1}` matches the previous token between zero and one times, as many times as possible, giving back as needed (greedy)
- `\d` matches a digit (equivalent to `[0-9]`)
 - `{2,4}` matches the previous token between 2 and 4 times, as many times as

QUICK REFERENCE

Search reference

- All Tokens
- ★ **Common Tokens** ✓
- General Tokens
- ⚓ Anchors
- ⊗ Meta Sequences
- ⌘ Quantifiers
- () Group Constructs
- [] Character Classes

A single character of: a, b or c	<code>[abc]</code>
A character except: a, b or c	<code>[^abc]</code>
A character in the range: a-z	<code>[a-z]</code>
A character not in the range: a-z	<code>[^a-z]</code>
A character in the range: a-z or A-Z	<code>[a-zA-Z]</code>
Any single character	<code>.</code>
Alternate - match either a or b	<code>a b</code>
Any whitespace character	<code>\s</code>
Any non-whitespace character	<code>\S</code>

REGULAR EXPRESSION

regex101.com

4 matches (92 steps, 0.0ms)

```
/[a-z]{2,3}\s{0,1}\d{2,4}\b
```

/g



TEST STRING

I'll fly with mh12 or BA123 or af1234 or EK 77 or
klm 87 or lh 1230 or maybe I go by foot.

REGEX FLAGS

global

Don't return after first match



REGEX FLAGS

global

Don't return after first match



multi line

^ and \$ match start/end of line

insensitive

Case insensitive match



REGULAR EXPRESSION

regex101.com

6 matches (104 steps, 0.1ms)

```
⋮ / [a-z]{2,3}\s{0,1}\d{2,4}\b
```

```
/ gi
```

REGEX FLAGS

global
Don't return after first match

multi line
^ and \$ match start/end of line

insensitive
Case insensitive match

TEST STRING

I'll fly with mh12 or BA123 or af1234 or EK 77 or
klm 87 or lh 1230 or maybe I go by foot.

MATCH INFORMATION

[Match 1](#) 14-18 mh12

[Match 2](#) 22-27 BA123

[Match 3](#) 31-37 af1234

[Match 4](#) 41-46 EK 77

[Match 5](#) 50-56 klm 87

[Match 6](#) 60-67 lh 1230



Submission Order

You can specify the order in which swimlanes are run. ⓘ

Extract Text Features

Base Metadata **Custom RegEx Pattern** Link Data Text Analytics - Start Text Analytics - Topic Creation Text Analytics - Bool Rule Creation Information Node Notes

Please enter a valid RegEx pattern here - you have to enclose it in / and you can specify a RegEx Flag.*

Only create a Feature if the Pattern occurs n times:

▼ ▲

Add Tables summarizing the findings to the Results

▼ Snippet Context Window for the Pattern (Optional)

Enables you to create an additional output table that contains next to the extracted pattern some surrounding text to better enable you to judge if your pattern worked as you intended.

To enter a custom name for this table please right click the step in the flow > Expand Output Ports and then connect your desired output table to the new port.

Do you want to create an additional table containing some context around the found RegEx Pattern?

Number of characters extracted before and after the Occurrence:

▼ ▲

▼ Feature Association with Target (Optional)

If you have a numerical binary target variable with values 0 and 1 then you can create additional statistics to show the association of the target level with the feature.

Do you have a binary numeric Target variable?

Please select the Target variable from the Input D...*

@ target

Minimum Target Mean:

▼ ▲

Maximum Target Mean

▼ ▲



Submission Order

You can specify the order in which swimlanes are run.

Extract Text Features

Base Metadata Custom RegEx Pattern Link Data Text Analytics - Start Text Analytics - Topic Creation Text Analytics - Bool Rule Creation Information Node Notes

Please enter a valid RegEx pattern here - you have to enclose it in / and you can specify a RegEx Flag: *

Only create a Feature if the Pattern occurs n times:

Add Tables summarizing the findings to the Results

Snippet Context Window for the Pattern (Optional)

Enables you to create an additional output table that contains next to the extracted pattern some surrounding text to better enable you to judge if your pattern worked as you intended.

To enter a custom name for this table please right click the step in the flow > Expand Output Ports and then connect your desired output table to the new port.

Do you want to create an additional table containing some context around the found RegEx Pattern?

Number of characters extracted before and after the Occurrence:

Feature Association with Target (Optional)

If you have a numerical binary target variable with values 0 and 1 then you can create additional statistics to show the association of the target level with the feature.

Do you have a binary numeric Target variable?

Please select the Target variable from the Input D... *

Minimum Target Mean:

Maximum Target Mean

Target Association with Perl Regular expression Query: /b[a-z]{2,3}\s(0,1)d{2,4}b/i

Target_Mean	Doc_CNT	NPos	NNeg	Occurance	Text Snippets: Detected Occurrence Instance Examples in Text
Lowcase					
100.00%	51	53	0	mh370	o be from MH370 - Nation ircraft to flight MH370 Á%ÁÁ Ma rmed from MH370; relative om Flight MH370 http://t. is from #M
83.89%	9	8	1	utc2015	01.04.01 UTC2015-08-05 15: 01.04.01 UTC2015-08-05 15: 01.04.01 UTC2015-08-05 15: 01.04.01 UTC2015-08-05 06:
Propcase					
100.00%	51	52	0	MH370	o be from MH370 - Nation ircraft to flight MH370 Á%ÁÁ Ma rmed from MH370; relative om Flight MH370 http://t. is from #M
83.89%	9	8	1	UTC2015	01.04.01 UTC2015-08-05 15: 01.04.01 UTC2015-08-05 15: 01.04.01 UTC2015-08-05 15: 01.04.01 UTC2015-08-05 06:

Target Association with Perl Regular expression Query:/:accident|fire|outbreak|rock|bag|ship|food|lost|tsunami|slide/|

Target_Mean	Doc_CNT	NPos	NNeg	Occurance	Text Snippets: Detected Occurance Instance Examples in Text
Lowcase					
100.00%	29	30	0	outbreak	onnaires' outbreak in South An outbreak of Legionnaires' the fatal outbreak of Legion An outbreak of Legionnaires' the fatal outbreak of Legio
76.02%	336	298	94	fire	GrahamWP fired a gun! A apartment fire #NewYork The Bush fires in CA are mia Bush fires please e d Osborn. Fire extinguis were bush fires n
75.00%	12	9	3	lost	OLATE&LOST + HER LOV ilies who lost loved one ays. I've lost count s. H bomb lost 70 miles ine and I lost my glasse #Govt has lost an #E
70.27%	72	52	22	accident	ne of the accident.....who airplane accident https:// le die in accident https://t airplane accident. I Vehicle Accident Congestio airp
53.66%	38	22	19	rock	in steep rocky terrain tripped. Brock obliterated @RockBottomRadFM As a ki d. Yes Brockton gets \$ ller_Chi/@RockefellerUni rism on '@Rockefe
50.00%	39	20	20	food	k with no food or water of whole foods clothing 'illegal food.' anctioned food: Vladimir y Western food en masse ioning of food and water
42.86%	68	30	40	ship	and Friendship in Her Ne Ocean Township apartment ved in my ship around th ng partnerships #AfterHa nt #leadership #smallbiz ling 3939 ships
40.00%	24	10	15	tsunami	@Eric_Tsunami worry about y ake & Tsunami want some tsunami take out quake snd tsunami early war me like a tsunami! Thank yo eard? The t
39.29%	56	22	34	slide	Landslide caused by sever ed a #landslide' http://t like a mudslide? like a mudslide hah th the mudslide and the g Rubber Mudslide! Still la
8.11%	89	9	102	bag	@Zak_Bagans pets r like r ?? @Zak_Bagans http:// @Zak_Bagans this is Sab e arrived Bago ece of cabbage????????? hiking garbage-bot (des #Fl
Propcase					
100.00%	26	26	0	outbreak	onnaires' outbreak in South An outbreak of Legionnaires' the fatal outbreak of Legion An outbreak of Legionnaires' the fatal outbreak of Legio
87.50%	15	14	2	Accident	I Vehicle Accident Congestio AirPlane #Accident #JetEngin Horrible Accident Man Died Horrible Accident Man Died M0cBA Car Accident tee%_
78.22%	276	237	66	fire	GrahamWP fired a gun! A apartment fire #NewYork The Bush fires in CA are mia Bush fires please e were bush fires near whe ced after fired d
70.51%	70	55	23	Fire	d Osborn. Fire extinguis d Osborn. Fire extinguis Bush Fires are scary.... 95: 'Bush Fires.' http:// scitech: #Firefighters r ; BLAZING Firem
62.26%	53	33	20	accident	ne of the accident.....who airplane accident https:// le die in accident https://t airplane accident. airplane accident. Traffic accide
54.55%	11	6	5	FIRE	ildfire): FIRE UPDATE: R HELLFIRE EP - SILENTMIND ST FOREST FIRES! PRAY! T A FOREST FIRE THAT CANN ASH TRUCK FIRE BITCH IS FIRE MOCK WI
52.94%	17	9	8	rock	in steep rocky terrain tripped. Brock obliterated d. Yes Brockton gets \$ #electro #rock #comingso reshapes rocks at the a ars loose rocks f
48.57%	34	17	18	food	k with no food or water of whole foods clothing 'illegal food.' anctioned food: Vladimir y Western food en masse ioning of food and water
43.14%	51	22	29	slide	Landslide caused by sever ed a #landslide' http://t like a mudslide? like a mudslide hah th the mudslide and the g Rubber Mudslide! Still la
42.62%	60	26	35	ship	and Friendship in Her Ne Ocean Township apartment ved in my ship around th ng partnerships #AfterHa nt #leadership #smallbiz ling 3939 ships
42.11%	17	8	11	Rock	@RockBottomRadFM As a ki ller_Chi/@RockefellerUni rism on '@Rockefeller_Ch @RockBottomRadFM Is one Bang Bang Rock and Roll' #RockyFire Updat
41.18%	16	7	10	tsunami	want some tsunami take out quake snd tsunami early war me like a tsunami! Thank yo eard? The tsunami's... http & the tsunami: The late m
8.11%	32	3	34	Bag	@Zak_Bagans pets r like r ?? @Zak_Bagans http:// @Zak_Bagans this is Sab e arrived Bago #Flood in Bago Myanmar ts Zipper Bags Coffee h Sho
6.94%	70	5	67	bag	ece of cabbage????????? hiking garbage-bot (des dio @Heavybag201 @batt %_ body bags%_ - Body Handbags for Wome a Vickers bags: machi

New Options View Open Save All

SAS Studio compute context

Start Page *_ulr_swhee_nlp_desaster_Prediction_tweets_007.sas * Flow.flw x +

Run Cancel Add View

Flow Generated Code Submission

>> Submission Order

You can specify the order in which swimlanes are run. ⓘ



Extract Text Features

< Base Metadata Custom RegEx Pattern **Link Data** Text Analytics - Start Text Analytics - Topic Creation Text Analytics - Bool Rule >

Collect additional information from the links in the tweets. This option requires you to have enabled the Options for concatenated and separated columns.

Please note for this step to work your environment needs to be able to make calls to the open internet.

Please be also aware that this step **can take a loot of time to run** as the individual sites have to be called and their output need to be parsed.

The following five features are extracted for each link:

- HTTP Status Code (basically is it reachable or not)
- Title of the Webpage
- Description of the Webpage
- URL of the Webpage (handy if URL shorteners were used)
- Owner of the site

Do you want to collect metadata from Links in the text?

Do you want to allow Unverified Requests (Warning potential impact: Breach of Confidentiality & Breach of Integrity)?



Submission Order

You can specify the order in which swimlanes are run. ⌚

Enable submission order

Extract Text Features

Base Metadata Custom RegEx Pattern Link Data **Text Analytics - Start** Text Analytics - Topic Creation Text Analytics - Bool Rule Creation Information Node Node >

The additional information derived here is only available if you have SAS Visual Text Analytics licensed.

To detect the sentiment and extract text topics you have to select the language detection option.

Do you want to use Text Analytics? (license required)

Do you want to automatically detect the text language?

Yes

No

Please select the language of your text:

English

Text Profiling

Do you want to profile your text?

Compare your text corpus to reference corpus profiles (Not available for all languages yet, raises a warning accordingly)

Add Word and Sentence count per Document and Language to the Results

Create a feature for the number of sentences in the Text

Create a feature for the count of tokens in the longest sentence

Sentiment detection

Do you want to detect the text sentiment?

Create Plot of Sentiment by Languages

Text Concept Extraction

Selecting SAS Predefined Concepts also enables you to use these as features in the customization options for the Text Topic Creation.

Do you want to apply the SAS Predefined Concepts?

Select Predefined Concepts you wish applie... 9 sele...

Noun Group

Organization

Percent

Person

Place

Time

Create Plot of Extracted SAS Predefined Concepts for each Language

Do you want to create a concated column of all matched text for each pre defined concept type?

Custom Text Concept Extraction

Please ensure that you have validated your Custom Concepts before using this step.

To add the table containing your Custom Concepts right click the step in the flow > Expand Input Ports and then connect your desired input table to the new

Supplying your own Custom Concepts also enables you to use these features in the customization options for the Text Topic Creation.

Do you want to apply custom concepts?

Derive Predictors from Boolean Term Rules

The screenshot displays the SAS Studio interface. At the top, the title bar reads "SAS® Studio - Develop SAS Code". Below it, a menu bar includes "Options", "View", "Open", and "Save All". The main workspace shows a workflow with three nodes: "TWEETS_BR_K W", "Extract Text Features", and "Tweets_BR_K W_ETM". The "Extract Text Features" node is highlighted, and its configuration pane is open, showing the "Text Analytics - Bool Rule Creation" tab. This pane contains several options, with checkboxes for "Do you want to have Topics created for you?", "Do you want us the Text Topic Creation Best Practise?", and "Create Scree Plots of the SVD for each language".

On the right side of the interface, a "Submission Order" panel is visible, with the text: "You can specify the order in which swimlanes are run." and a toggle for "Enable submission order".

Below the workflow, the documentation for the "PROC BOOLRULE Procedure" is displayed. The left sidebar lists various SAS procedures, with "PROC BOOLRULE Features" selected. The main content area shows the following text:

The BOOLRULE Procedure

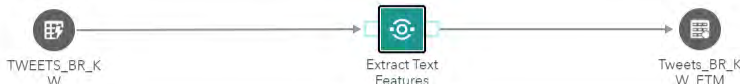
Overview Getting Started Syntax Details Examples References

PROC BOOLRULE Features

The BOOLRULE procedure processes large-scale transactional data in parallel to achieve efficiency and scalability. The following list summarizes the basic features of PROC BOOLRULE.

- Boolean rules are automatically extracted from large-scale transactional data.
- The extracted rules can be easily understood and tuned by humans.
- Important features are identified for each category.
- Imbalanced data are handled robustly.
- Binary-class and multiclass categorization are supported.
- Events for defining labels for documents are supported.
- All processing phases use a high degree of multithreading.

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Last updated: June 12, 2018



Submission Order

You can specify the order in which swimlanes are run.

Extract Text Features

Do you want to leverage BoolRule Creation to create additional Features?

Do you want use the Term-by-Document Matrix from the Topic Creation?

Please select a target variable: *

target

Please select the Type of your Target Variable: *

Binary

Customization

Enter the Minimum G-Score needed for a Positive Term to be considered for Rule Extraction:

10

Enter the M Value for computing Estimated Precision for Positive Terms:

10

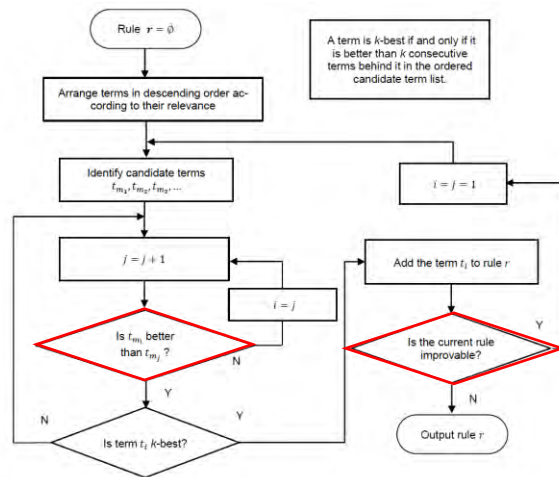
Enter the Minimum G-Score needed for a Negative Term to be considered for Rule Extraction:

10

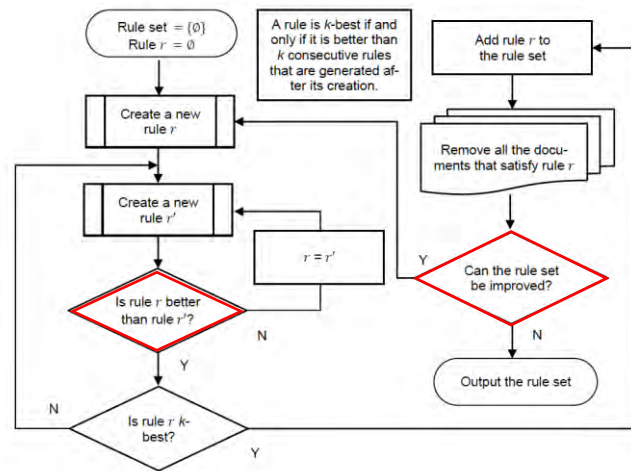
Enter the M Value for computing Estimated Precision for Negative Terms:

10

Term Ensemble Process for Creating a Rule



Rule Ensemble for Creating a Rule Set



Tasks



SAS Tasks : My Tasks

- Tasks
- ▶ Econometrics
- ▶ Forecasting
- ▶ Optimization and Network Analysis
- ▶ Prepare Data
- ▶ SAS Viya Cloud Analytic Services
- ▶ SAS Viya Econometrics
- ▶ SAS Viya Evaluate and Implement Models
- ▶ SAS Viya Forecasting
- ▶ SAS Viya Machine Learning
- ▶ SAS Viya Optimization and Network Analysis
- ▶ SAS Viya Prepare and Explore Data
- ▶ SAS Viya Statistics
- ▶ SAS Viya Text Analytics
 - Boolean Rules
 - Segmentation
 - Text Parsing and Topic Discovery
 - Text Scoring
 - Text Summarization

Start Page x +

GET STARTED

Program in SAS

Build a flow

Import data

Query data

NEW Explore new features in SAS Studio

LEARN

Learn SAS Studio - videos, tutorials and training

Learn SAS programming

STAY CONNECTED

Join the community

Request a feature

RECENTS

_ulr_swee_nlp_desaster_Prediction_tweets_008.sas
/Users/viyademo04a/My Folder/My Snippets Sep 6, 2022, 5:35:52 PM **RULES**
CASUSER **Extract Text Features.step**
/Public/Custom Steps Sep 2, 2022, 11:04:59 AM **_ulr_swee_nlp_desaster_Prediction_tweets_007.sas**
/Users/viyademo04a/My Folder/My Snippets Sep 6, 2022, 5:31:02 PM **TWEETS_BR_KW_ETM**
WORK Sep 6, 2022, 2:15:58 PM **_ULR_TA_BoolRule_Desaster_tweet_004.sas**
/Users/viyademo04a/My Folder/My Snippets Aug 12, 2022, 3:48:37 PM **TWEETS**
WORK **_ulr_swee_nlp_desaster_Prediction_tweets_006.sas**
/Users/viyademo04a/My Folder/My Snippets Sep 1, 2022, 5:12:51 PM **Extract Tweet Metadata.step**
Custom Steps Aug 4, 2022, 4:23:25 PM

New Options View Open Save All

SAS Studio compute context

Tasks



Type to filter...

SAS Tasks My T...

- Econometrics
- Forecasting
- Optimization and f
- Prepare Data
- SAS Viya Cloud An
- SAS Viya Econome
- SAS Viya Evaluate a
- SAS Viya Forecasti
- SAS Viya Machine l
- SAS Viya Optimiza
- SAS Viya Prepare a
- SAS Viya Statistics
- SAS Viya Text Anal
- Boolean Rules**
- Segmentation
- Text Parsing an
- Text Scoring

Start Page Boolean Rules.ctlk x +

Run Cancel Stop Copy to My Tasks

Code to Flow

Data Options Output Information

Code Log

Edit Code

Data

PUBLIC._ULR_TWEETS_DESASTER...

Filter: (none)

The input table contains:

- Unparsed text
- Term-by-document matrix

Language:

English

Roles

Text variable: *

Add a character variable

Task Console (2)

- Text variable: - Requires exactly one variable
- Nominal target: - Requires exactly one variable

```
1 /* Code for this task cannot be generated because of an error.
2  * Please use the Task Console to view and fix the errors.
3  */
4
```

Tasks

Type to filter list

SAS Tasks My Tasks

- Econometrics
- Forecasting
- Optimization and Network A
- Prepare Data
- SAS Viya Cloud Analytic Ser
- SAS Viya Econometrics
- SAS Viya Evaluate and Imple
- SAS Viya Forecasting
- SAS Viya Machine Learning
- SAS Viya Optimization and N
- SAS Viya Prepare and Explor
- SAS Viya Statistics
- SAS Viya Text Analytics
- Boolean Rules
- Segmentation
- Text Parsing and Topic Di
- Text Scoring
- Text Summarization
- Statistical Process Control
- Statistics
- Visualize Data

Start Page * Boolean Rules.ctlk x +

Run Cancel Copy to My Tasks + Code to Flow

Data Options Output Information

Language: English

Roles

Text variable: *

text

Key variable:

Automatically create

Select variable

Target

Select the type of target:

One or more binary targets

One multi-level nominal target

Binary targets: *

target

Level of interest: *

1

Code Log

Edit Code

```

1 /*
2 *
3 * Task code generated by SAS® Studio 6.0
4 *
5 * Generated on '10/12/22, 4:09 PM'
6 * Generated on server 'sas-launcher-63f5a0da-238b-4678-9137-6ab452e32e5c-42'
7 * Generated on SAS platform 'Linux LIN X64 5.4.0-1080-azure'
8 * Generated on SAS version 'V.04.00M0P081522'
9 * Generated on browser 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit
10 * Generated on web client 'https://extviya4.emea.sas.com/SASstudio/main?loc
11 */
12
13 ods noproctitle;
14 libname _tmpcas_ cas caslib="CASUSER";
15
16 /* Create unique key variable */
17 data _tmpcas_._preProcessedData;
18   if _N_=1 then
19     do;
20       _mult=10**(int(log10(_NTHREADS_))+1);
21       retain _mult;
22       drop _mult;
23     end;
24   set PUBLIC._ULR_TWEETS_DESASTER_PRED_KAGGLE;
25   __uniqueid__=_THREADID+(_N*_mult);
26 run;
27
28 /* Load default English stop list */
29 proc casutil;
30   load casdata="en_stoplist.sashdat" INCASLIB="referencedata"
31     casout="_stoplist_" outcaslib="CASUSER" replace;
32   quit;
33
34 proc textmine data=_tmpcas_._preProcessedData;
35   var txtv.

```

Tasks



< SAS Tasks : My Tasks >

- Econometrics
- Forecasting
- Optimization and Network A
- Prepare Data
- SAS Viya Cloud Analytic Ser
- SAS Viya Econometrics
- SAS Viya Evaluate and Imple
- SAS Viya Forecasting
- SAS Viya Machine Learning
- SAS Viya Optimization and N
- SAS Viya Prepare and Explor
- SAS Viya Statistics
- SAS Viya Text Analytics
- Boolean Rules
- Segmentation
- Text Parsing and Topic Di
- Text Scoring
- Text Summarization
- Statistical Process Control
- Statistics
- Visualize Data

Start Page * Boolean Rules.ctlk x +

Run + Code to Flow

Data Options Output Information

Minimum number of occurrences to keep a term: *

 v ^

 Use the log to weight the cells of the term-by-document matrix

Weight terms by:

 Specify a start or stop list

 Start list

 Stop list

 Default list

 Custom list

 Specify a synonym list

 Specify a multi-word terms list

Rules Extraction

Minimum number of documents in which a term must appear to be used in a rule: *

 v ^

Minimum g-score: *

 v ^

 Specify separate minimum g-score for negative terms

Minimum m value for computing estimated precision: *

 v ^

Code Log

```

1  /*
2  *
3  * Task code generated by SAS® Studio 6.0
4  *
5  * Generated on '10/12/22, 4:09 PM'
6  * Generated on server 'sas-launcher-63f5a0da-238b-4678-9137-6ab452e32e5c-42'
7  * Generated on SAS platform 'Linux LIN X64 5.4.0-1080-azure'
8  * Generated on SAS version 'V.04.00M0P081522'
9  * Generated on browser 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit
10 * Generated on web client 'https://extviya4.emea.sas.com/SASstudio/main?loc
11 */
12
13 ods noproctitle;
14 libname _tmpcas_ cas caslib="CASUSER";
15
16 /* Create unique key variable */
17 data _tmpcas_._preProcessedData_
18     if _N_=1 then
19         do;
20             _mult=10**(int(log10(_NTHREADS_))+1);
21             retain _mult;
22             drop _mult;
23         end;
24     set PUBLIC._ULR_TWEETS_DESASTER_PRED_KAGGLE;
25     __uniqueid__=_THREADID+(_N*_mult);
26 run;
27
28 /* Load default English stop list */
29 proc casutil;
30     load casdata="en_stoplist.sashdat" INCASLIB="referencedata"
31         casout="_stoplist_" outcaslib="CASUSER" replace;
32     quit;
33
34 proc textmine data=_tmpcas_._preProcessedData_
35     var text;
36

```

Tasks

Type to filter list

SAS Tasks My Tasks

- Econometrics
- Forecasting
- Optimization and Network A
- Prepare Data
- SAS Viya Cloud Analytic Ser
- SAS Viya Econometrics
- SAS Viya Evaluate and Imple
- SAS Viya Forecasting
- SAS Viya Machine Learning
- SAS Viya Optimization and N
- SAS Viya Prepare and Explor
- SAS Viya Statistics
- SAS Viya Text Analytics
- Boolean Rules
- Segmentation
- Text Parsing and Topic Di
- Text Scoring
- Text Summarization
- Statistical Process Control
- Statistics
- Visualize Data

Start Page * Boolean Rules.ctlk x +

Run Cancel Copy to My Tasks Code to Flow

Data Options **Output** Information

Specify a CAS table: * Replace

Specify a CAS table: * Replace

Save parsed term information

Specify a CAS table: * Replace

Save parsing configuration (for Boolean rules scoring)

Specify a CAS table: * Replace

Rules Extraction

- Save rules
 - Specify a CAS table: * Replace
 - V4data.Rules
- Save rule term information
 - Specify a CAS table: * Replace
 - V4data.Terms
- Save candidate terms
 - Specify a CAS table: * Replace
 - V4data.Cterms

Code Log

```

12
13 ods noproctitle;
14 libname _tmpcas_ cas caslib="CASUSER";
15
16 /* Create unique key variable */
17 data _tmpcas_._preProcessedData_;
18   if _N_=1 then
19     do;
20       _mult=10**((int(log10(_NTHREADS_))+1);
21       retain _mult;
22       drop _mult;
23     end;
24   set PUBLIC._ULR_TWEETS_DESASTER_PRED_KAGGLE;
25   __uniqueid__=_THREADID+(_N*_mult);
26 run;
27
28 /* Load default English stop list */
29 proc casutil;
30   load casdata="en_stoplist.sashdat" INCASLIB="referencedata"
31     casout="_stoplist_" outcaslib="CASUSER" replace;
32   quit;
33
34 proc textmine data=_tmpcas_._preProcessedData_;
35   var text;
36   doc_id __uniqueid__;
37   parse stop=_tmpcas_._stoplist_ outparent=_tmpcas_._termByDoc_
38     outterms=_tmpcas_._terms_;
39 run;
40
41 proc boolrule data=_tmpcas_._termByDoc_ docinfo=_tmpcas_._preProcessedData_
42   docid= document _terminfo=_tmpcas_._terms_ _termid=_termnum;
43   docinfo id=__uniqueid__ _targets=(target) events=('1');
44   _terminfo id=key label=term;
45   output rules=V4data.Rules _ruleterms=V4data.Terms _candidateterms=V4data.Cterms;
46 run;
47

```

Tasks

Start Page Boolean Rules.ctlk x +

Run Cancel Copy to My Tasks Code to Flow

Data Options Output Information

Code Log Output Data (3)

Filter

CTERMS
Library: V4DATA

RULES
Library: V4DATA

TERMS
Library: V4DATA

Output Data

The following tables must use a CAS engine libref:

Parse Text

Save term-by-document matrix

Specify a CAS table: *

Save parsed term information

Specify a CAS table: *

Save parsing configuration (for Boolean rules scoring)

Specify a CAS table: *

Rules Extraction

Save rules

Specify a CAS table: *

V4data.Rules

Save rule term information

Specify a CAS table: *

V4data.Terms

Save candidate terms

Specify a CAS table: *

V4data.Cterms

Table rows: 183 Columns: 11 of 15 Rows 1 to 183

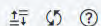
Enter expression

	TARGET...	RULE	TP	FP	SUP...	rTP	rFP	rSUP...	F1	PRECISI...	RI
97	1	distance	2005	385	2390	4	0	4	0.70...	0.8389121339	0.614...
98	1	fires	2009	385	2394	4	0	4	0.71...	0.8391812865	0.615...
99	1	gunman	2013	385	2398	4	0	4	0.71...	0.8394495413	0.616...
100	1	vietnam	2017	385	2402	4	0	4	0.71...	0.8397169026	0.617...
101	1	disrupt	2021	385	2406	4	0	4	0.71...	0.8399833749	0.619...
102	1	disaster	2052	417	2469	31	32	63	0.71...	0.8311057108	0.628...
103	1	death	2087	455	2542	35	38	73	0.71...	0.821007081	0.639...
104	1	palestinian	2090	455	2545	3	0	3	0.71...	0.8212180747	0.640...
105	1	typhoon	2093	455	2548	3	0	3	0.72...	0.8214285714	0.641...
106	0	bag	27	0	27	27	0	27	0.01...	1	0.
107	0	ebay	59	1	60	32	1	33	0.02...	0.9833333333	0.013...
108	0	body	92	3	95	33	2	35	0.04...	0.9684210526	0.021...
109	0	song	121	5	126	29	2	31	0.05...	0.9603174603	0.028...
110	0	traumatize	154	8	162	33	3	36	0.06...	0.950617284	0.035...
111	0	crush	180	10	190	26	2	28	0.07...	0.9473684211	0.041...
112	0	wreck	222	15	237	42	5	47	0.09...	0.9367088608	0.051...
113	0	listen	236	15	251	14	0	14	0.10...	0.9402390438	0.054...
114	0	soul	250	15	265	14	0	14	0.10...	0.9433962264	0.057...
115	0	bag	269	16	285	19	1	20	0.11...	0.9438596491	0.062...
116	0	panic	293	18	311	24	2	26	0.12...	0.9421221865	0.067...
117	0	not & ~murd...	308	18	326	15	0	15	0.13...	0.9447852761	0.071...
118	0	panic	351	24	375	43	6	49	0.14...	0.936	0.

Available Data Sources Import

_ULR_TWEETS_DES_RULES

Filter



Details

Sample Data

Sample rows:

 _ULR_DESASTER_PRED_TWEETS_P...
 10/12/22 08:55 AM • gercar

 _ULR_EN_INSURANCE_CHURN
 10/12/22 08:55 AM • gercar

 _ULR_TWEETS_DES_RULES
 10/12/22 05:08 PM • viyadem...

 _ULR_TWEETS_DESASTE
 10/12/22 08:55 AM • gercar

 942E4544-D08F-490A-9
 10/12/22 08:55 AM • gercar

 ABCD
 10/12/22 09:00 AM • gercar

 ALL_ACTS
 10/12/22 08:55 AM • gercar

 ALL_LIBRARIES
 10/12/22 08:55 AM • gercar

 ALL_OBJECTS
 10/12/22 08:55 AM • gercar

 ALL_RELATIONSHIPS
 10/12/22 08:55 AM • gercar

 ALL_SERVERS
 10/12/22 08:55 AM • gercar

 ALL_TABLES
 10/12/22 08:55 AM • gercar

 BANK_DEMO_DATA
 10/12/22 08:55 AM • gercar

- Actions >
- Unload
- View authorization
- Edit authorization
- Delete
- Add to import
- Download table

TAR...	TAR...	TAR...	TAR...	RULE...	RULE	TP	FP	SUP...	rTP	rFF
1	2	target	1	1	mh370	70	0	70	70	0
1	2	target	1	2	hiroshima	155	1	156	85	1
1	2	target	1	3	northern	215	1	216	60	0
				4	bomber	269	2	271	54	1
				5	migrant	309	2	311	40	0
				6	legionn...	349	2	351	40	0
				7	california	422	7	429	73	5
				8	severe	455	7	462	33	0
				9	derailm...	484	7	491	29	0
				10	airport	511	7	518	27	0
				11	israeli	537	7	544	26	0
				12	bombing	563	7	570	26	0
				13	kill	657	20	677	94	13
				14	refugio	679	20	699	22	0
				15	crisis	700	20	720	21	0
				16	fukushima	719	20	739	19	0
				17	train & ...	748	20	768	29	0
				18	village	766	20	786	18	0
				19	wildfire	788	21	809	22	1
				20	earthqu	821	25	846	33	4

Boolean Rule Result Browser (NLP Disaster Prediction Twitter)

Editing

Page 1

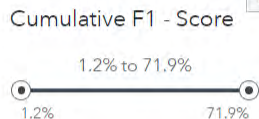
Drag a data item or control here to create a page prompt.

Filters: 81.5%; 100.0% > 6; 318 > 1.2%; 71.9% > 0.6%; 63.9%

Frequency
162

Total Precision
0.82

Target Value
0 | 1



Support, TargetMean by rule



rID	target	rule	rSupport	TargetMean	rTP	rFP	FP	TP	precision	F-1 score	recall	Support
1	1	mh370	70	100.0%	70	0	0	70	100.0%	4.2%	2.1%	70
2	1	hiroshima	86	98.8%	85	1	1	155	99.4%	9.1%	4.7%	156
3	1	northern	60	100.0%	60	0	1	215	99.5%	12.4%	6.6%	216
4	1	bomber	55	98.2%	54	1	2	269	99.3%	15.2%	8.2%	271
5	1	migrant	40	100.0%	40	0	2	309	99.4%	17.3%	9.5%	311
6	1	legionnaire	40	100.0%	40	0	2	349	99.4%	19.3%	10.7%	351
7	1	california	78	93.6%	73	5	7	422	98.4%	22.9%	12.9%	429
8	1	severe	33	100.0%	33	0	7	455	98.5%	24.4%	13.9%	462
9	1	derailment	29	100.0%	29	0	7	484	98.6%	25.8%	14.8%	491
10	1	airport	27	100.0%	27	0	7	511	98.6%	27.0%	15.7%	518
11	1	israeli	26	100.0%	26	0	7	537	98.7%	28.2%	16.5%	544
12	1	bombing	26	100.0%	26	0	7	563	98.8%	29.4%	17.2%	570
13	1	kill	107	87.9%	94	13	20	657	97.0%	33.3%	20.1%	677
14	1	refugio	22	100.0%	22	0	20	679	97.1%	34.3%	20.8%	699
15	1	crisis	21	100.0%	21	0	20	700	97.2%	35.1%	21.4%	720
16	1	fukushima	19	100.0%	19	0	20	719	97.3%	35.9%	22.0%	739
17	1	train & derail	29	100.0%	29	0	20	748	97.4%	37.1%	22.9%	768
18	1	village	18	100.0%	18	0	20	766	97.5%	37.8%	23.5%	786

Boolean Rule Result Browser (NLP Disaster Prediction Twitter)

Drag a data item or control here to create a page prompt.

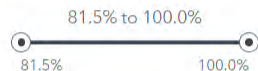
Filters: 81.5%; 100.0% > 6; 318 > 1.2%; 71.9% > 0.6%; 63.9% > 1 x

Frequency
84

Total Precision
0.83

Target Value

Cumulative Precision



Cumulative F1 - Score



Cumulative Recall



Min Rule Support



Support, TargetMean by rule



rID	target	rule	rSupport	TargetMean	rTP	rFP	FP	TP	precision	F-1 score	recall	Support
1	1	mh370	70	100.0%	70	0	0	70	100.0%	4.2%	2.1%	70
2	1	hiroshima	86	98.8%	85	1	1	155	99.4%	9.1%	4.7%	156
3	1	northern	60	100.0%	60	0	1	215	99.5%	12.4%	6.6%	216
4	1	bomber	55	98.2%	54	1	2	269	99.3%	15.2%	8.2%	271
5	1	migrant	40	100.0%	40	0	2	309	99.4%	17.3%	9.5%	311
6	1	legionnaire	40	100.0%	40	0	2	349	99.4%	19.3%	10.7%	351
7	1	california	78	93.6%	73	5	7	422	98.4%	22.9%	12.9%	429
8	1	severe	33	100.0%	33	0	7	455	98.5%	24.4%	13.9%	462
9	1	derailment	29	100.0%	29	0	7	484	98.6%	25.8%	14.8%	491
10	1	airport	27	100.0%	27	0	7	511	98.6%	27.0%	15.7%	518
11	1	israeli	26	100.0%	26	0	7	537	98.7%	28.2%	16.5%	544
12	1	bombing	26	100.0%	26	0	7	563	98.8%	29.4%	17.2%	570
13	1	kill	107	87.9%	94	13	20	657	97.0%	33.3%	20.1%	677
14	1	refugio	22	100.0%	22	0	20	679	97.1%	34.3%	20.8%	699
15	1	crisis	21	100.0%	21	0	20	700	97.2%	35.1%	21.4%	720
16	1	fukushima	19	100.0%	19	0	20	719	97.3%	35.9%	22.0%	739
17	1	train & derail	29	100.0%	29	0	20	748	97.4%	37.1%	22.9%	768
18	1	village	18	100.0%	18	0	20	766	97.5%	37.8%	23.5%	786

Boolean Rule Result Browser (NLP Disaster Prediction Twitter)

Editing

Page 1

Drag a data item or control here to create a page prompt.

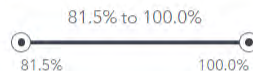
Filters: 81.5%; 100.0% > 6; 318 > 1.2%; 71.9% > 0.6%; 63.9% > 0 x

Frequency
78

Total Precision
0.82

Target Value

Cumulative Precision



Cumulative F1 - Score



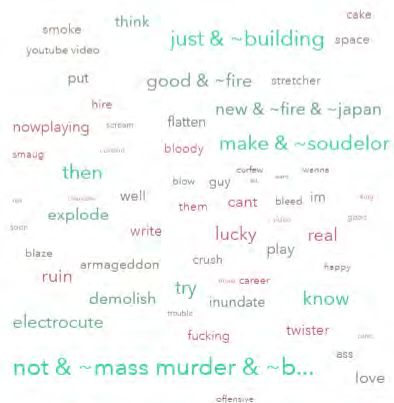
Cumulative Recall



Min Rule Support



Support, TargetMean by rule



rID	target	rule	rSupport	TargetMean	rTP	rFP	FP	TP	precision	F-1 score	recall	Support
107	0	ebay	33	97.0%	32	1	1	59	98.3%	2.7%	1.4%	60
108	0	body	35	94.3%	33	2	3	92	96.8%	4.2%	2.1%	95
109	0	song	31	93.5%	29	2	5	121	96.0%	5.4%	2.8%	126
110	0	traumatize	36	91.7%	33	3	8	154	95.1%	6.9%	3.6%	162
112	0	wreck	47	89.4%	42	5	15	222	93.7%	9.7%	5.1%	237
113	0	listen	14	100.0%	14	0	15	236	94.0%	10.3%	5.5%	251
114	0	soul	14	100.0%	14	0	15	250	94.3%	10.9%	5.8%	265
117	0	not & ~murder ...	15	100.0%	15	0	18	308	94.5%	13.3%	7.1%	326
119	0	aftershock	19	94.7%	18	1	25	369	93.7%	15.7%	8.5%	394
120	0	pick	19	94.7%	18	1	26	387	93.7%	16.4%	9.0%	413
122	0	obliteration	24	91.7%	22	2	38	470	92.5%	19.5%	10.9%	508
123	0	obliterate	57	86.0%	49	8	46	519	91.9%	21.2%	12.0%	565
124	0	want	86	84.9%	73	13	59	592	90.9%	23.8%	13.7%	651
125	0	let	63	85.7%	54	9	68	646	90.5%	25.7%	15.0%	714
126	0	reã	23	91.3%	21	2	70	667	90.5%	26.4%	15.4%	737
127	0	character	12	100.0%	12	0	70	679	90.7%	26.8%	15.7%	749
128	0	king	12	100.0%	12	0	70	691	90.8%	27.2%	16.0%	761
129	0	content	22	90.9%	20	2	72	711	90.8%	27.9%	16.5%	783

Boolean Rule Result Browser (NLP Disaster Prediction Twitter)

Editing

Page 1

Drag a data item or control here to create a page prompt.

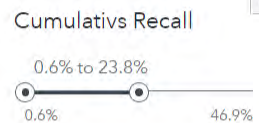
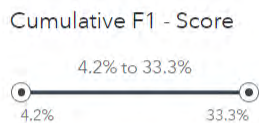
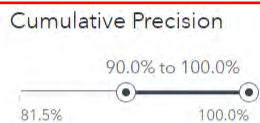
Filters: 90.0%; 100.0% > 0.6%; 23.8% > 53; 107 > 4.2%; 33.3%

Frequency
9

Total Precision
0.9

Target Value

0 | 1



Support, TargetMean by rule

hiroshima



rID	target	rule	rSupport	TargetMean	rTP	rFP	FP	TP	precision	F-1 score	recall	Support
2	1	hiroshima	86	98.8%	85	1	1	155	99.4%	9.1%	4.7%	156
3	1	northern	60	100.0%	60	0	1	215	99.5%	12.4%	6.6%	216
4	1	bomber	55	98.2%	54	1	2	269	99.3%	15.2%	8.2%	271
7	1	california	78	93.6%	73	5	7	422	98.4%	22.9%	12.9%	429
121	0	love	71	85.9%	61	10	36	448	92.6%	18.7%	10.4%	484
123	0	obliterate	57	86.0%	49	8	46	519	91.9%	21.2%	12.0%	565
124	0	want	86	84.9%	73	13	59	592	90.9%	23.8%	13.7%	651
125	0	let	63	85.7%	54	9	68	646	90.5%	25.7%	15.0%	714
135	0	scream	59	84.7%	50	9	90	852	90.4%	32.4%	19.7%	942



Boolean Rule Result Browser (NLP Disaster Prediction Twitter)

Drag a data item or control here to create a page prompt.

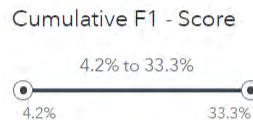
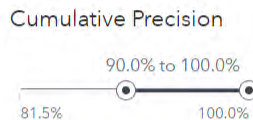
Filters: 90.0%; 100.0% > 0.6%; 23.8% > 53; 107 > 4.2%; 33.3%

Frequency
9

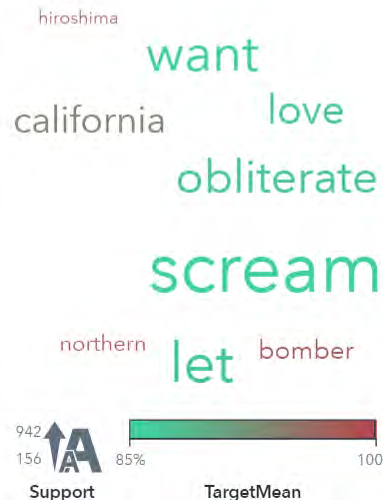
Total Precision
0.9

Target Value

0 | 1



Support, TargetMean by rule



rID	target	rule	rSupport	TargetMean	rTP	rFP	FP	TP	precision	F-1 score	recall	Support
2	1	hiroshima	86	98.8%	85	1	1	155				
3	1	northern	60	100.0%	60	0	1	215				
4	1	bomber	55	98.2%	54	1	2	269				
7	1	california	78	93.6%	73	5	7	422				
121	0	love	71	85.9%	61	10	36	448				
123	0	obliterate	57	86.0%	49	8	46	519				
124	0	want	86	84.9%	73	13	59	592				
125	0	let	63	85.7%	54	9	68	646				
135	0	scream	59	84.7%	50	9	90	852				

- Remove all role assignments
- Show object title
- Maximize view
- Delete
- Duplicate
- Duplicate as >
- Move to >
- Add link >
- Export >
- Copy link...
- Save to Objects pane
- Change List table to >

- Image
- PDF
- Excel workbook
- Data

A1 | 90.0% ≤ precision ≤ 100.0%

rID	target	rule	rSupport	TargetMean	rTP	rFP	FP	TP	precision	F-1 score	recall	Suppo
2	1	hiroshima	86	98.8%	85	1	1	155	99.4%	9.1%	4.7%	15
3	1	northern	60	100.0%	60	0	1	215	99.5%	12.4%	6.6%	21
4	1	bomber	55	98.2%	54	1	2	269	99.3%	15.2%	8.2%	27
7	1	california	78	93.6%	73	5	7	422	98.4%	22.9%	12.9%	42
121	0	love	71	85.9%	61	10	36	448	92.6%	18.7%	10.4%	48
123	0	obliterate	57	86.0%	49	8	46	519	91.9%	21.2%	12.0%	56
124	0	want	86	84.9%	73	13	59	592	90.9%	23.8%	13.7%	65
125	0	let	63	85.7%	54	9	68	646	90.5%	25.7%	15.0%	71
135	0	scream	59	84.7%	50	9	90	852	90.4%	32.4%	19.7%	94

```

proc sql noprint;
  select ruleid , compress(translate(strip rule),',','&'),' ~')
    into : ranks separated by '|',
         : terms separated by '|';
  from tmpcas.rules
  order by ruleid;
quit;

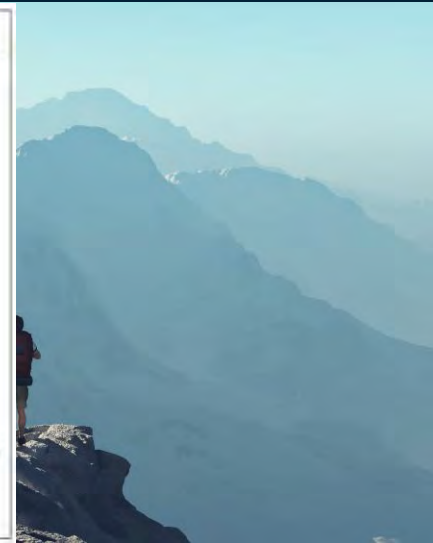
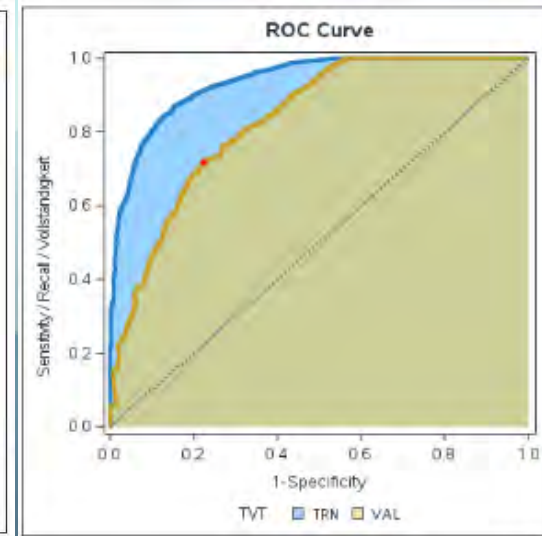
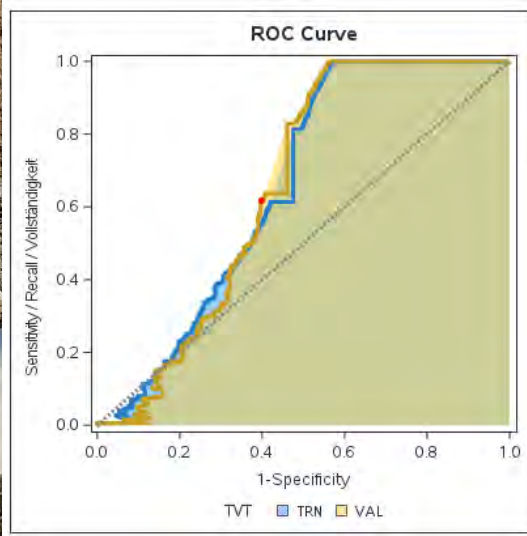
%let N=&sqllobs.;
%put &=N.;
%put &=ranks.;
%put &=terms.;

data ABT_BR;
  set ABT;
  %do i=1 %to &n.;
    BR &i.= (find(&text., "%scan(&terms., &i., '|')", 'i') gt 0);
    Label BR_&i.= "BR &i.: %scan(&terms., &i., '|')";
  %end;

run;
  
```

This SQL and Data Step attaches binary variables for the selected terms indicating "1" whenever a term appears in the text.

Welche features verbessern hier die Klassifikation?



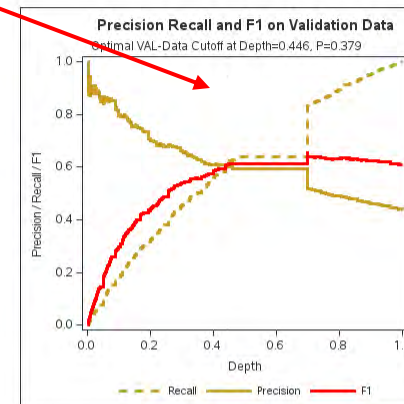
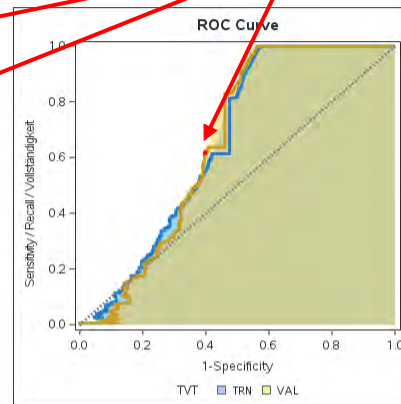
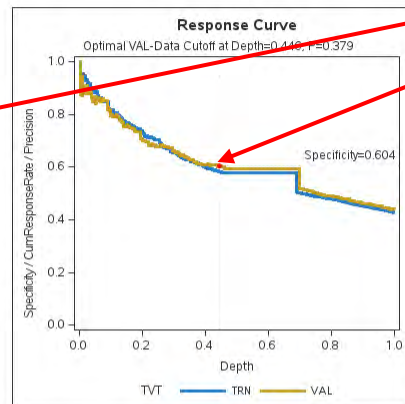
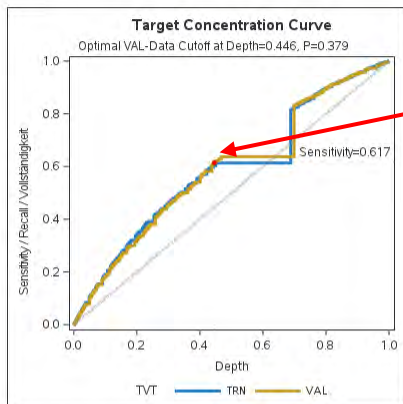
To answer this question, we need to attempt to climb the ROC

0. Step: VA TA

Assessment for Model a: Repaired Data (N=7575) Gradient Boosting with 6 Features (6TextTopics), Dependent Variable: Target

Corrupted Data

TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.36446	0.41863	0.52829	0.61853	0.56986	1.44953	0.16383	0.42671	0.28578
VAL	0.44635	0.37946	0.61732	0.60404	0.61061	1.38304	0.17097	0.43668	0.30350



Training Data, Cutoff used: 0.419

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN			
	Predicted			Total
	target	0	1	
0	2302	737	3039	43.43
	13.90	24.25	57.33	
	75.75	68.31	38.17	
1	1068	1194	2262	20.15
	22.52	47.21	52.79	42.67
	31.69	61.83		
Total	3370	1931	5301	63.57
	36.43	100.00		

Validation Data, Cutoff used: 0.379

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL			
	Predicted			Total
	target	0	1	
0	879	402	1281	38.65
	17.68	68.62	31.38	56.33
	69.82	61.73	39.61	
1	380	613	993	16.71
	26.94	38.27	61.73	43.67
	30.18	60.39		
Total	1259	1015	2274	55.36
	44.64	100.00		

Selected Prediction Features: Top 11

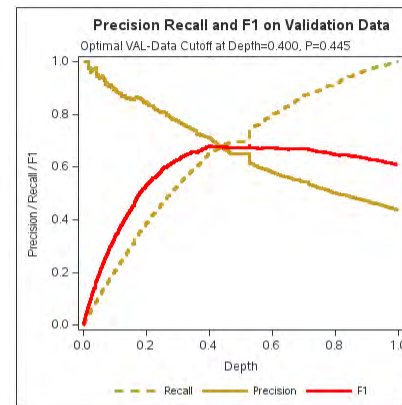
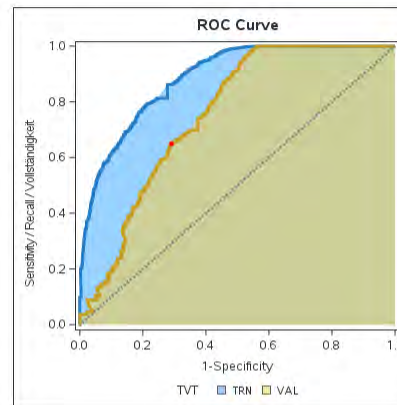
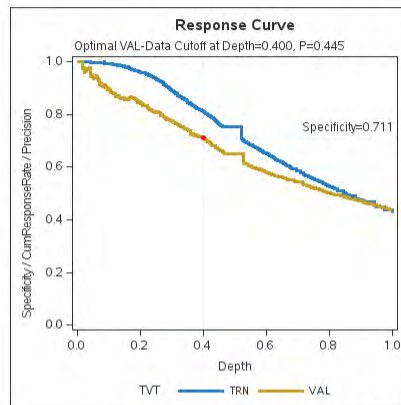
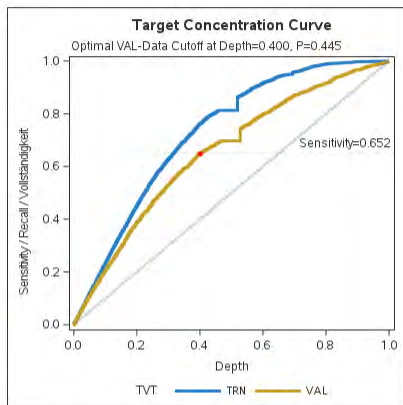
No	Variable Name and Label	RelImp	Number of Levels
1	_etm__Col1_: "not, +even, blood, +	1.00	2958
2	_etm__Col3_: "+wildfire, californi	0.78	754
3	_etm__Col5_: "+fire, +forest, +tru	0.71	2413
4	_etm__Col2_: "+detonate, army, +ol	0.63	1565
5	_etm__Col4_: "+confirm, mh370, wre	0.51	903
6	_etm__Col6_: "reddit, +quarantine,	0.25	2176

1. Step: VTA MS Pipeline

Assessment for Model 1: Gradient Boosting with 25 Features [25TextTopics], Dependent Variable: Target

Corrupted Data

	TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.41873	0.42033	0.78214	0.79591	0.78896	1.86791	0.36342	0.42610	0.63323	
VAL	0.40028	0.44498	0.65180	0.71147	0.68033	1.62838	0.25153	0.43692	0.44670	



Training Data, Cutoff used: 0.420

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN			
	Predicted			
	target	0	1	Total
0	2449	432	2881	
	48.78	8.61	57.39	
	85.01	14.99		
	84.01	20.52		
1	466	1673	2139	
	9.28	33.33	42.61	
	21.79	78.21		
	15.99	79.48		
Total	2915	2105	5020	
	58.07	41.93	100.00	

Validation Data, Cutoff used: 0.445

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL			
	Predicted			
	target	0	1	Total
0	965	249	1214	
	44.76	11.55	56.31	
	79.49	20.51		
	74.57	28.89		
1	329	613	942	
	15.26	28.43	43.69	
	34.93	65.07		
	25.43	71.11		
Total	1294	862	2156	
	60.02	39.98	100.00	

Selected Prediction Features: Top 11

No	Variable Name and Label	RelImp	Number of Levels
1	_etm_COL5: "+fire, +forest, +truck	1.00	2353
2	_etm_COL23: "+go, +flame, +siren,	0.91	2660
3	_etm_COL10: "+bomb, hiroshima, ato	0.91	1897
4	_etm_COL18: "+scream, im, internal	0.86	1242
5	_etm_COL21: "+train, +life, +derai	0.84	2012
6	_etm_COL2: "+wildfire, california,	0.74	679
7	_etm_COL22: "still, +war, +world,	0.61	3211
8	_etm_COL7: "+bag, +body, +cross, +	0.56	1857
9	_etm_COL14: "+man, +car, +flame, +	0.54	3012
10	_etm_COL1: "amp, rt, +please, +bac	0.52	3473
11	_etm_COL4: "+confirm, wreckage, mh	0.48	473

Selected Prediction Features: Top 12-22

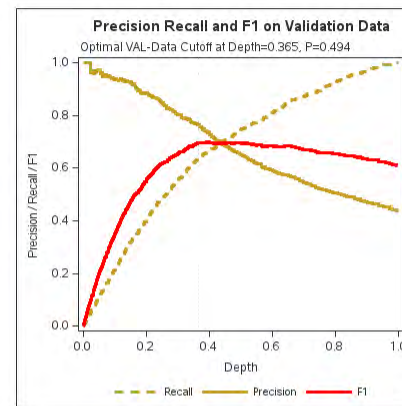
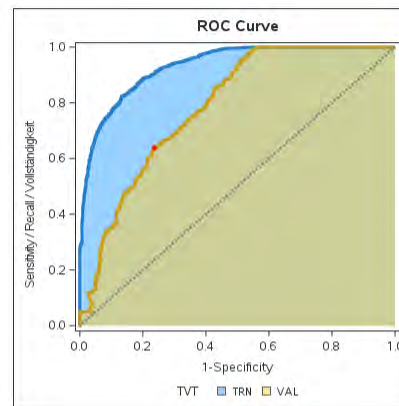
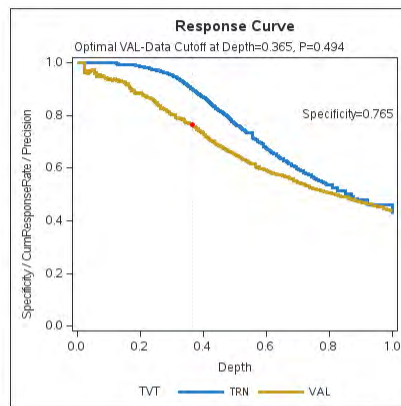
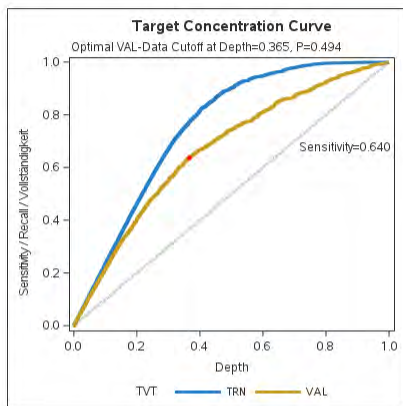
No	Variable Name and Label	RelImp	Number of Levels
12	_etm_COL19: "+wreck, +word, +stock	0.40	1424
13	_etm_COL25: "+migrant, +rescuer, h	0.40	1729
14	_etm_COL17: "+video, youtube, play	0.36	1690
15	_etm_COL16: "+wave, +hot, +hijack,	0.34	1553
16	_etm_COL20: "+crush, +woman, +girl	0.32	1253
17	_etm_COL9: "+legionnaire, +family,	0.30	385
18	_etm_COL6: "reddit, +quarantine, c	0.27	2152
19	_etm_COL13: "+burn, +build, not, +	0.25	1912
20	_etm_COL3: "+detonate, army, +old,	0.22	1176
21	_etm_COL11: "+disaster, obama, typ	0.15	888
22	_etm_COL15: "+oil, +spill, +big, +	0.15	509

2. Step: VTA MS Pipeline

Assessment for Model 3: Gradient Boosting with 76 Features [66TextTopics], Dependence Variable: Target

Corrupted Data

TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.40498	0.44398	0.82328	0.86621	0.84420	2.03289	0.41830	0.42610	0.72887
VAL	0.36549	0.49405	0.64013	0.76523	0.69711	1.75141	0.27464	0.43692	0.48774



Training Data, Cutoff used: 0.444

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN			
	Predicted			
target	0	1	Total	
0	2609	272	2881	
	51.97	5.42	57.39	
	90.56	9.44		
	87.32	13.39		
1	379	1760	2139	
	7.55	35.06	42.61	
	17.72	82.28		
	12.68	86.61		
Total	2988	2032	5020	
	59.52	40.48	100.00	

Validation Data, Cutoff used: 0.494

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL			
	Predicted			
target	0	1	Total	
0	1029	185	1214	
	47.73	8.58	56.31	
	84.76	15.24		
	75.22	23.48		
1	339	603	942	
	15.72	27.97	43.69	
	35.99	64.01		
	24.78	76.52		
Total	1368	788	2156	
	63.45	36.55	100.00	

Selected Prediction Features: Top 11

No	Variable Name and Label	RelImp	Number of Levels
1	_etm_COL47: "+thunderstorm, severe	1.00	2496
2	_etm_COL5: "+fire, +forest, +truck	0.91	2353
3	_etm_COL66: "+good, +know, +way, +	0.88	4066
4	_etm_COL10: "+bomb, hiroshima, ato	0.87	1897
5	_etm_COL2: "+wildfire, california,	0.84	679
6	_etm_COL18: "+scream, im, internal	0.72	1242
7	_etm_COL36: "+suicide, +kill, saud	0.65	1440
8	_etm_COL59: "+new, +collide, full,	0.58	4075
9	_etm_COL21: "+train, +life, +derai	0.57	2012
10	_etm_COL72: "+charge, +boy, mansla	0.53	3352
11	_etm_COL23: "+go, +flame, +siren,	0.46	2660

Selected Prediction Features: Top 12-22

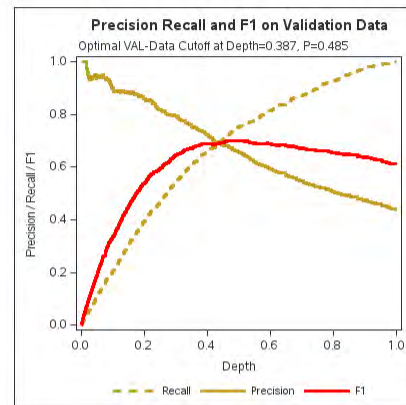
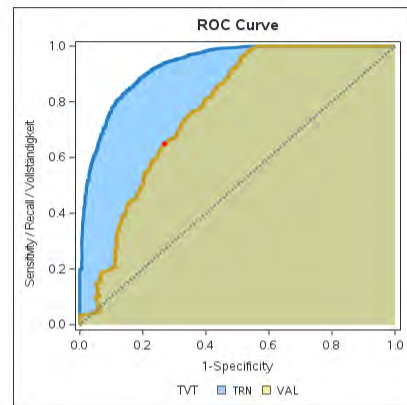
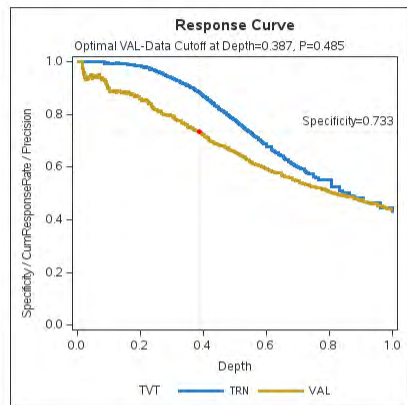
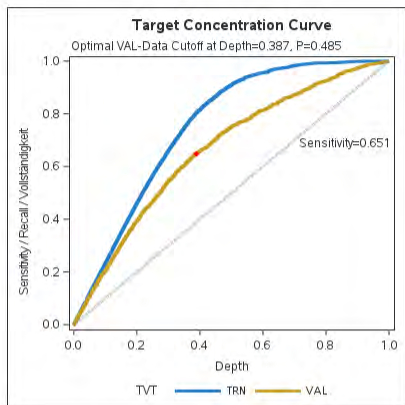
No	Variable Name and Label	RelImp	Number of Levels
12	_etm_COL56: "+day, +riot, +ruin, r	0.43	4244
13	_etm_COL71: "+see, +panic, +attack	0.43	3621
14	_etm_COL60: "+blow, +electrocute,	0.41	3469
15	_etm_COL46: "+people, +panic, +smo	0.40	4020
16	_etm_COL31: "+not, +even, blood, +f	0.40	2854
17	_etm_COL33: "+accident, airplane,	0.40	2584
18	_etm_COL28: "police, +wound, +susp	0.36	1534
19	_etm_COL4: "+confirm, wreckage, mh	0.33	473
20	_etm_COL62: "+come, +smoke, here,	0.32	3790
21	_etm_COL27: "+hive, +see, tragedy,	0.30	3102
22	_etm_COL53: "+fear, +ambulance, +h	0.30	1918

2a. Step: VTA MS Pipeline

Model 2.a Repaired Data (N=7575): Gradient Boosting with 76 Features [76TextTopics], Dependent Variable: Target

Clean Data

TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.43105	0.43615	0.85013	0.84158	0.84583	1.97223	0.41908	0.42671	0.73101
VAL	0.38742	0.48493	0.65055	0.73326	0.68943	1.67918	0.26313	0.43668	0.46710 (prev. 0.48774)



Training Data, Cutoff used: 0.436

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN			
	Predicted			
target	0	1	Total	
0	2677	362	3039	50.50
	6.83	57.33		
	88.09	11.91		
	88.76	15.84		
1	339	1923	2262	6.40
	36.28	42.67		
	14.99	85.01		
	11.24	84.16		
Total	3016	2285	5301	56.89
	43.11	100.00		

Validation Data, Cutoff used: 0.485

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL			
	Predicted			
target	0	1	Total	
0	1046	235	1281	46.00
	10.33	56.33		
	81.65	18.35		
	75.04	26.70		
1	348	645	993	15.30
	28.36	43.67		
	35.05	64.95		
	24.96	73.30		
Total	1394	880	2274	61.30
	38.70	100.00		

Selected Prediction Features: Top 11

No	Variable Name and Label	RelImp	Number of Levels
1	_etm_Col51: "+thunderstorm, seve	1.00	2539
2	_etm_Col28: "+suicide, +kill, sa	0.85	1608
3	_etm_Col5: "+fire, +forest, +tru	0.76	2413
4	_etm_Col67: "+blow, +time, +elec	0.73	4284
5	_etm_Col44: "*", +let, +want, do	0.73	3569
6	_etm_Col24: "+train, +life, dera	0.72	2436
7	_etm_Col10: "+bomb, hiroshima, a	0.65	1886
8	_etm_Col9: "+scream, im, arianag	0.64	967
9	_etm_Col62: "+new, +collide, +we	0.63	4553
10	_etm_Col38: "+love, +collide, +y	0.62	2644
11	_etm_Col73: "+fuck, +back, +weap	0.60	3781

Selected Prediction Features: Top 12-22

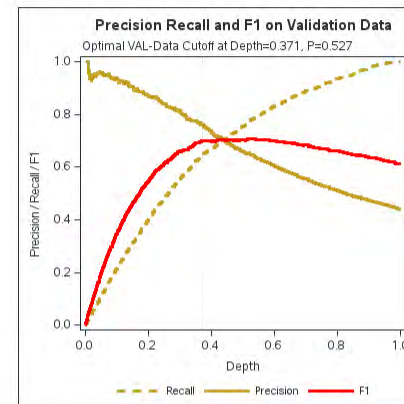
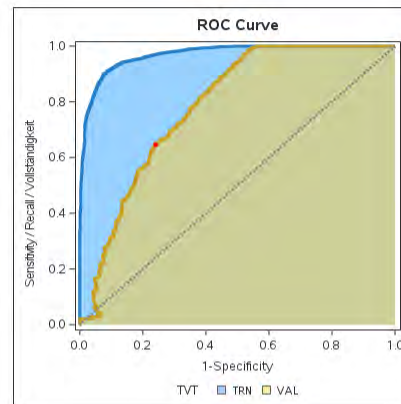
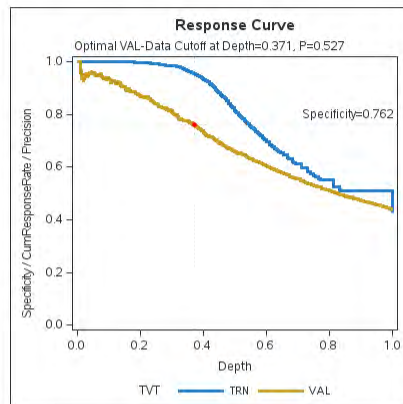
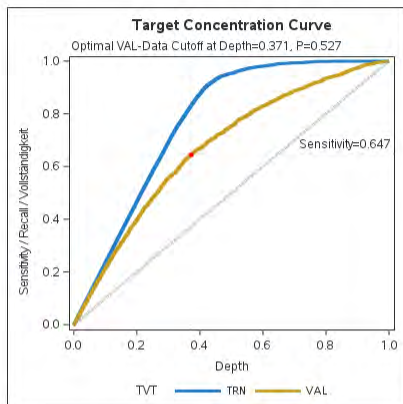
No	Variable Name and Label	RelImp	Number of Levels
12	_etm_Col22: "police, +wind, +sus	0.59	1862
13	_etm_Col30: "now, +right, +panic	0.58	3920
14	_etm_Col52: "+day, +riot, +good,	0.56	4445
15	_etm_Col66: "+flood, +work, +rai	0.55	3362
16	_etm_Col1: "not, +even, blood, +	0.55	2958
17	_etm_Col29: "emergency, +plan, +	0.50	3217
18	_etm_Col7: "+bag, +body, +cross,	0.49	1636
19	_etm_Col32: "+see, +back, +life,	0.49	4382
20	_etm_Col76: "+charge, +boy, mans	0.46	4026
21	_etm_Col3: "+wildfire, californi	0.45	754
22	_etm_Col25: "+go, +siren, +let,	0.45	3313

3a. Step: 147 Features

3.a Repaired Data (N=7575): Gradient Boosting with 147 Features #Terms @Terms URLs WordCnt CharCnt 76TextTopics, Dependent Variable: Target

Clean Data

TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.42501	0.43253	0.91026	0.91389	0.91207	2.14171	0.48524	0.42671	0.84642
VAL	0.37071	0.52697	0.64653	0.76157	0.69935	1.74401	0.27581	0.43668	0.48962



„Our new features“ not provided automatically in VA or VTA

Training Data, Cutoff used: 0.433

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN			
	Predicted			
target	0	1	Total	
0	2845	194	3039	53.67
	53.67	3.66	57.33	93.62
	6.38	8.62	93.25	8.62
1	206	2056	2262	3.89
	38.79	42.67	9.11	90.89
	6.75	91.38	6.75	91.38
Total	3051	2250	5301	57.56
	42.44	100.00		

Validation Data, Cutoff used: 0.527

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL			
	Predicted			
target	0	1	Total	
0	1080	201	1281	47.49
	8.84	56.33	84.31	15.69
	23.87	75.42	75.42	23.87
1	352	641	993	15.48
	28.19	43.67	15.48	28.19
	64.55	24.58	24.58	76.13
Total	1432	842	2274	62.97
	37.03	100.00		

Selected Prediction Features: Top 11

No	Variable Name and Label	RelImp	Number of Levels
1	_etm_N_Links: Number of Links in th	1.00	5
2	_etm_Col28: "+suicide, +kill, sa	0.64	1608
3	_etm_Col51: "+thunderstorm, seve	0.54	2539
4	_etm_chrctr_cnt: Number of Characte	0.51	176
5	_etm_Col5: "+fire, +forest, +tru	0.49	2413
6	_etm_Col3: "+wildfire, californi	0.46	754
7	_etm_Col24: "+train, +life, dera	0.38	2436
8	_etm_Col10: "+bomb, hiroshima, a	0.38	1886
9	_etm_Col22: "police, +wind, +sus	0.37	1862
10	_etm_Col34: "+accident, +airplan	0.34	3202
11	_etm_Col7: "+bag, +body, +cross,	0.33	1636

Selected Prediction Features: Top 12-22

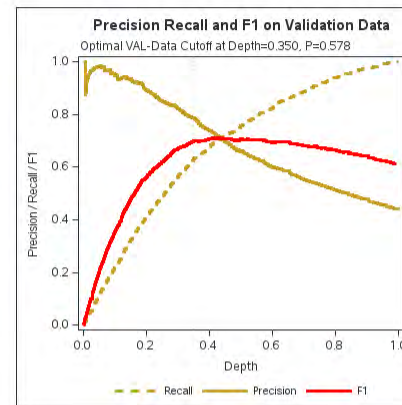
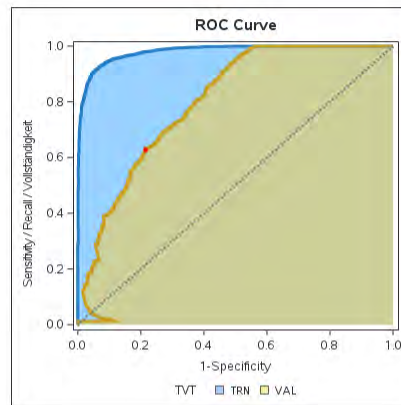
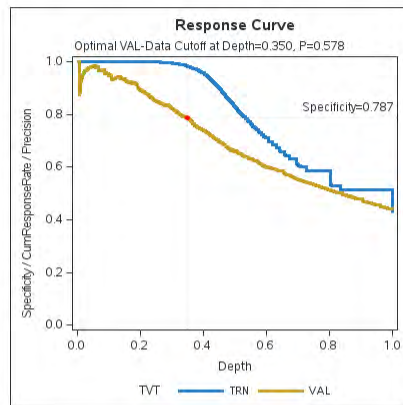
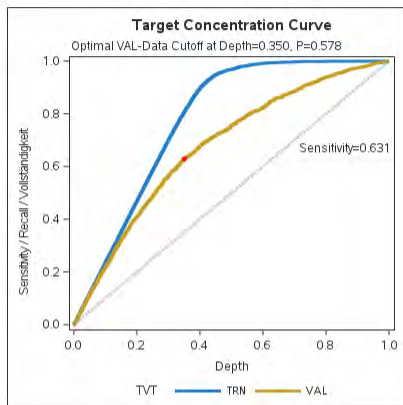
No	Variable Name and Label	RelImp	Number of Levels
12	_etm_Col75: "+know, +good, +let,	0.32	4187
13	_etm_Col30: "+now, +right, +panic	0.30	3920
14	_etm_Col52: "+day, +riot, +good,	0.30	4445
15	_etm_Col70: "+year, %, +time, f	0.29	4384
16	_etm_Col38: "+love, +collide, +y	0.27	2644
17	_etm_Col36: "+mass, +murderer, +	0.26	2455
18	_etm_AtSign_3: 3. user mention in t	0.26	118
19	_etm_Col60: "+rescue, +hostage,	0.26	3400
20	_etm_Col73: "+fuck, +back, +weap	0.25	3781
21	_etm_Col67: "+blow, +time, +elec	0.25	4284
22	_etm_Col44: "+, +let, +want, do	0.24	3569

4a. Step: 149 Features

Repaired Data (N=7575): Gradient Boosting with 149 Features (#Terms @Terms URLs WordCnt CharCnt **Sentiment** 76TextTopics), Dependent Variable: Target

Clean Data

TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.42558	0.43233	0.92750	0.92996	0.92873	2.17937	0.50192	0.42671	0.87551
VAL	0.35048	0.57797	0.63142	0.78670	0.70056	1.80157	0.28094	0.43668	0.49871



Training Data, Cutoff used: 0.432

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN		
	Predicted		
target	0	1	Total
0	2881	158	3039
	54.35	2.98	57.33
	94.80	5.20	
	94.61	7.00	
1	164	2098	2262
	3.09	39.58	42.67
	7.25	92.75	
	5.39	93.00	
Total	3045	2256	5301
	57.44	42.56	100.00

Validation Data, Cutoff used: 0.578

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL		
	Predicted		
target	0	1	Total
0	1111	170	1281
	48.86	7.48	56.33
	86.73	13.27	
	75.17	21.36	
1	367	626	993
	16.14	27.53	43.67
	36.96	63.04	
	24.83	78.64	
Total	1478	796	2274
	65.00	35.00	100.00

Selected Prediction Features: Top 11

No	Variable Name and Label	RelImp	Number of Levels
1	_etm_sentiment_score: Score value f	1.00	14
2	_etm_cooc_Link_4: Co-Occurence Link	0.82	2
3	_etm_prcntUtd: Percentage used of t	0.78	176
4	_etm_Col5_: "+fire, +forest, +tru	0.64	2413
5	_etm_Col3_: "+wildfire, californi	0.59	754
6	_etm_Col10_: "+bomb, hiroshima, a	0.58	1886
7	_etm_Col51_: "+thunderstorm, seve	0.53	2539
8	_etm_Col75_: "+know, +good, +let,	0.50	4187
9	_etm_Col24_: "+train, +life, dera	0.45	2436
10	_etm_Col22_: "police, +wind, +sus	0.45	1862
11	_etm_N_Links: Number of Links in th	0.43	5

Selected Prediction Features: Top 12-22

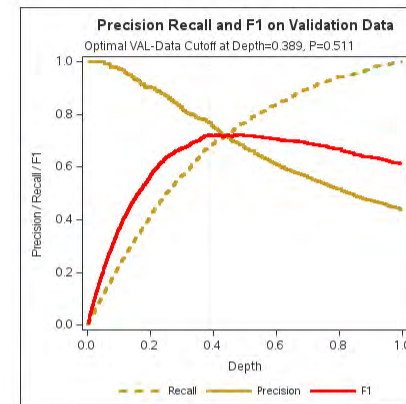
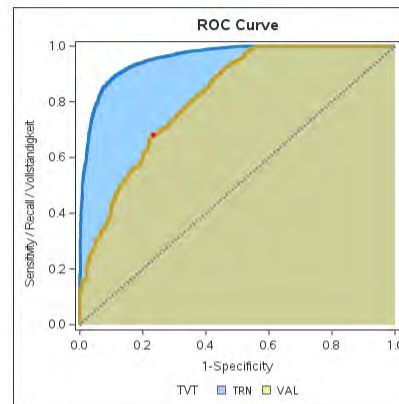
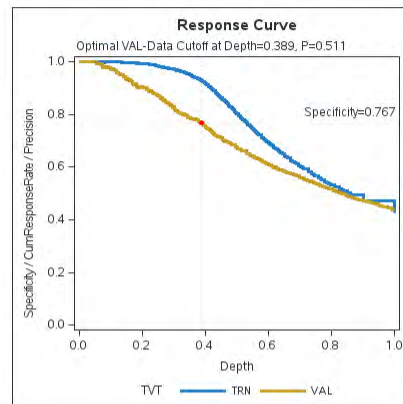
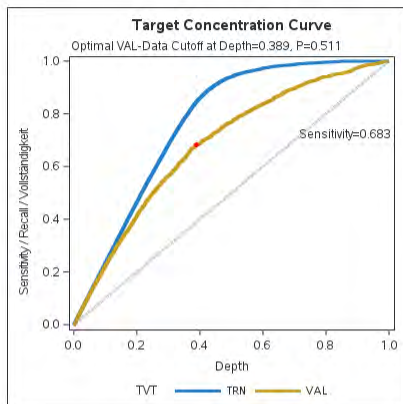
No	Variable Name and Label	RelImp	Number of Levels
12	_etm_Col30_: "now, +right, +panic	0.39	3920
13	_etm_chrctr_cnt: Number of Characte	0.38	176
14	_etm_Col52_: "+day, +riot, +good,	0.37	4445
15	_etm_Col7_: "+bag, +body, +cross,	0.36	1636
16	_etm_Col46_: "debris, +find, reun	0.35	2298
17	_etm_Col34_: "+accident, +airplan	0.34	3202
18	_etm_Col44_: "*, +let, +want, do	0.31	3569
19	_etm_Col9_: "+scream, im, arianag	0.30	967
20	_etm_Col73_: "+fuck, +back, +weap	0.29	3781
21	_etm_Col72_: "+say, +world, +elec	0.28	4730
22	_etm_wrd_cnt: Number of Words in a	0.28	31

4a. Step: 160 Features

Validation Data (N=7575): Gradient Boosting with 160 Features (PreDefConcepts + Terms @Terms URLs CharCmt Sentiment 76TextTopics), Dependent Variable

Clean Data

TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.42916	0.41800	0.89346	0.88835	0.89090	2.08185	0.46429	0.42671	0.80988
VAL	0.38874	0.51091	0.68278	0.76697	0.72243	1.75638	0.29404	0.43668	0.52197



Training Data, Cutoff used: 0.418

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN			
	Predicted			Total
target	0	1		
0	2785	254	3039	57.33
	52.54	4.79		
	91.64	8.36		
	92.04	11.16		
1	241	2021	2262	42.67
	4.55	38.12		
	10.65	89.35		
	7.96	88.84		
Total	3026	2275	5301	
	57.08	42.92	100.00	

Validation Data, Cutoff used: 0.511

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL			
	Predicted			Total
target	0	1		
0	1075	206	1281	56.33
	47.27	9.06		
	83.92	16.08		
	77.28	23.33		
1	316	677	993	43.67
	13.90	29.77		
	31.82	68.18		
	22.72	76.67		
Total	1391	883	2274	
	61.17	38.83	100.00	

Selected Prediction Features: Top 11

No	Variable Name and Label	RelImp	Number of Levels
1	_etm_concept: The concept that was	1.00	10
2	_etm_sentiment: Sentiment of the te	0.34	3
3	_etm_N_FullStop: Number of Periods	0.33	16
4	_etm_N_Links: Number of Links in th	0.23	5
5	_etm_Col51: "+thunderstorm, seve	0.22	2539
6	_etm_Col5: "+fire, +forest, +tru	0.22	2413
7	_etm_Col10: "+bomb, hiroshima, a	0.15	1886
8	_etm_Col28: "+suicide, +kill, sa	0.15	1608
9	_etm_Col7: "+bag, +body, +cross,	0.15	1636
10	_etm_Col62: "+new, +collide, +we	0.13	4553
11	_etm_chrctr_cnt: Number of Characte	0.13	176

Selected Prediction Features: Top 12-22

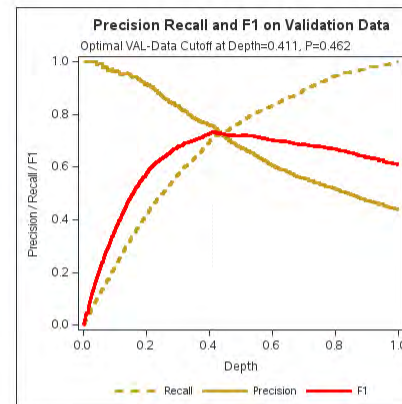
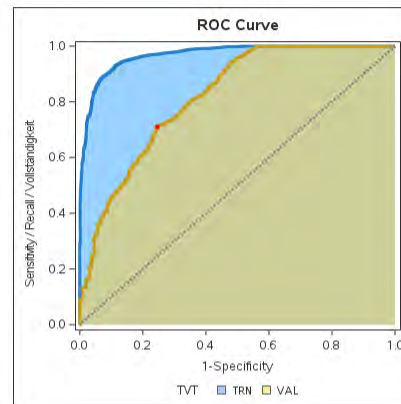
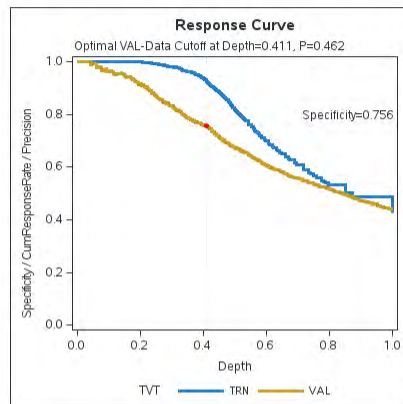
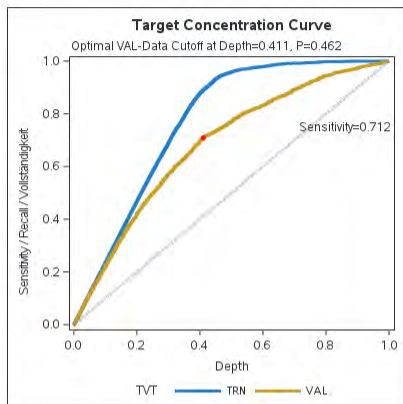
No	Variable Name and Label	RelImp	Number of Levels
12	_etm_Col44: "+, +let, +want, do	0.13	3569
13	_etm_sentiment_score: Score value f	0.12	14
14	_etm_Col32: "+see, +back, +life,	0.11	4382
15	_etm_Col67: "+blow, +time, +elec	0.10	4284
16	_etm_Col24: "+train, +life, dera	0.10	2436
17	_etm_Col73: "+fuck, +back, +weap	0.10	3781
18	_etm_cooc_Link_4: Co-Occurence Link	0.09	2
19	_etm_Col75: "+know, +good, +let,	0.09	4187
20	_etm_wrd_cnt: Number of Words in a	0.09	31
21	_etm_total_concepts: Total Number o	0.09	23
22	_etm_Col34: "+accident, +airplan	0.09	3202

5a. Step: 326 Features

(N=7575): Gradient Boosting with 326 Features | **BooleRules** PreDefConcepts #Terms URLS CharCnt CharCnt Sentiment 76TextTopics, Dependent

Clean Data

TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.44709	0.37785	0.93015	0.88776	0.90846	2.08048	0.48306	0.42671	0.84262
VAL	0.41117	0.46210	0.71198	0.75615	0.73340	1.73161	0.30081	0.43668	0.53400



Training Data, Cutoff used: 0.378

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN			
	Predicted			
	target	0	1	Total
0	2773	266	3039	52.31
1	159	2103	2262	3.00
Total	2932	2369	5301	55.31

Validation Data, Cutoff used: 0.462

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL			
	Predicted			
	target	0	1	Total
0	1053	228	1281	46.31
1	286	707	993	12.58
Total	1339	935	2274	58.88

Selected Prediction Features: Top 11

No	Variable Name and Label	RelImp	Number of Levels
1	BR1_0: Presence of TG1 assoc. BR	1.00	2
2	_etm_concept: The concept that was	0.35	10
3	_etm_cococ_Link_4: Co-Occurrence Link	0.20	2
4	BR1_20: BR1_20: mp	0.10	2
5	_etm_sentiment_score: Score value f	0.07	14
6	_etm_sentiment: Sentiment of the te	0.07	3
7	_etm_Col51_: "+thunderstorm, seve	0.06	2539
8	_etm_Col12_: "+amp, rt, +please, c	0.06	3648
9	_etm_total_concepts: Total Number o	0.06	23
10	_etm_Col44_: "+, +let, +want, do	0.05	3569
11	_etm_Col10_: "+bomb, hiroshima, a	0.05	1886

Selected Prediction Features: Top 12-22

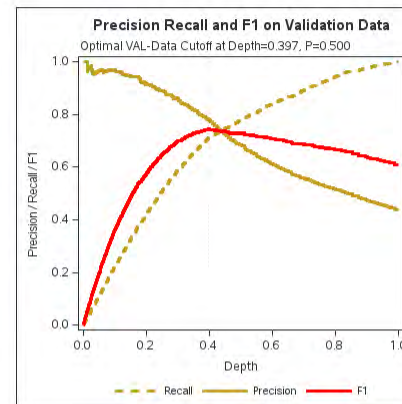
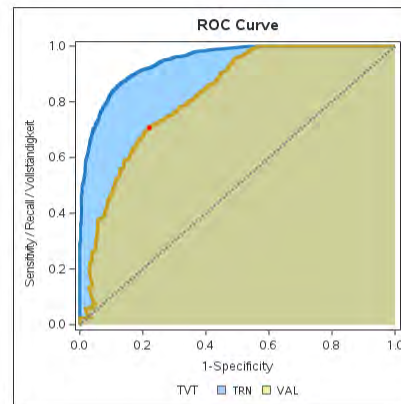
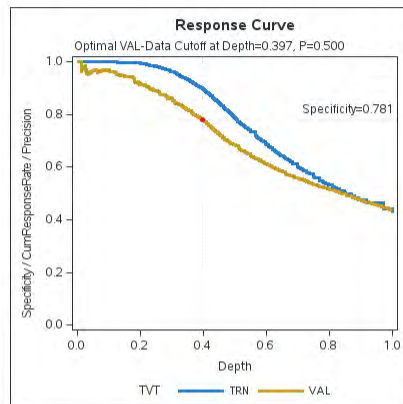
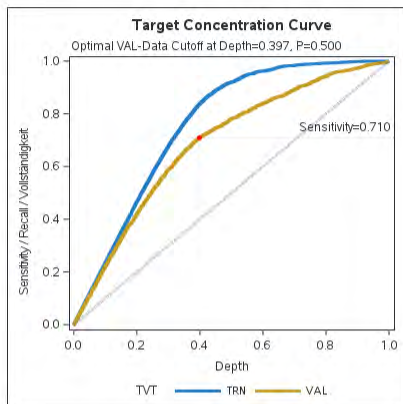
No	Variable Name and Label	RelImp	Number of Levels
12	_etm_Col9_: "+scream, im, arianag	0.05	967
13	_etm_Col5_: "+fire, +forest, +tru	0.05	2413
14	_etm_chrctr_cnt: Number of Characte	0.04	176
15	_etm_Col75_: "+know, +good, +let,	0.04	4187
16	_etm_Col62_: "+new, +collide, +we	0.04	4553
17	BR1_41: BR1_41: now	0.04	2
18	_etm_Col69_: "+say, +need, +stop,	0.04	4849
19	BR0_0: Presence of TG0 assoc. BR	0.04	2
20	_etm_Col68_: "+people, +panic, +s	0.04	4060
21	_etm_Col32_: "+see, +back, +life,	0.04	4382
22	_etm_Col28_: "+suicide, +kill, sa	0.04	1608

6a. Step: 550 Features

7575): Gradient Boosting with 550 Features ({Key words} BooleanRules PreDefConcepts #Terms URLs WordCnt CharCnt Sentiment 76TextTopics), Deper

Clean Data

TVT	Depth	P_Cutoff	Sensitivity	Specificity	f1	lift	benefit	PriorProb	KS
TRN	0.41615	0.45210	0.85809	0.87987	0.86885	2.06198	0.44194	0.42671	0.77089
VAL	0.39710	0.49997	0.70997	0.78073	0.74367	1.78790	0.31287	0.43668	0.55540



Training Data, Cutoff used: 0.452

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=TRN			
	Predicted			Total
target	0	1		
0	2774	265	3039	52.33
	52.33	5.00	57.33	
	91.28	8.72		
	89.63	12.01		
1	321	1941	2262	6.06
	6.06	36.62	42.67	
	14.19	85.81		
	10.37	87.99		
Total	3095	2206	5301	58.39
	58.39	41.61	100.00	

Validation Data, Cutoff used: 0.500

Frequency Percent Row Pct Col Pct	Table 1 of target by Predicted Controlling for TVT=VAL			
	Predicted			Total
target	0	1		
0	1083	198	1281	47.63
	47.63	8.71	56.33	
	84.54	15.46		
	78.94	21.95		
1	289	704	993	12.71
	12.71	30.96	43.67	
	29.10	70.90		
	21.06	78.05		
Total	1372	902	2274	60.33
	60.33	39.67	100.00	

Selected Prediction Features: Top 11

No	Variable Name and Label	RelImp	Number of Levels
1	KW1_C: Keyword TG1	1.00	80
2	KW0_C: Keyword TG0	0.94	107
3	BR1_0: Presence of TG1 assoc. BR	0.25	2
4	_etm_concept: The concept that was	0.19	10
5	_etm_N_Links: Number of Links in th	0.07	5
6	_etm_sentiment: Sentiment of the te	0.07	3
7	KW1_N: Number of Keywords TG1	0.04	7
8	_etm_Col44: "+, +let, +want, do	0.04	3569
9	KW0_N: Number of Keywords TG0	0.04	6
10	_etm_Col51: "+thunderstorm, seve	0.04	2539
11	_etm_wrd_cnt: Number of Words in a	0.03	31

Selected Prediction Features: Top 12-22

No	Variable Name and Label	RelImp	Number of Levels
12	_etm_Col38: "+love, +collide, +y	0.03	2644
13	BR1_62: BR1_62: fire	0.03	2
14	_etm_Col61: "+make, +deluge, +ri	0.03	3843
15	_etm_Col24: "+train, +life, dera	0.03	2436
16	_etm_Col71: "+see, +live, traged	0.03	3420
17	_etm_Col29: "+emergency, +plan, +	0.03	3217
18	_etm_chrctr_cnt: Number of Characte	0.03	176
19	_etm_Col62: "+new, +collide, +we	0.03	4553
20	_etm_Col70: "+year, ¥, +time, f	0.03	4384
21	_etm_Col50: "+school, hijacker,	0.03	2414
22	_etm_max_tokens_sentence: Number of	0.03	51

How can you use the custom Step

In SAS Studio on ssemontly

- Modelling in ModelStudio

Steps



Type to filter list

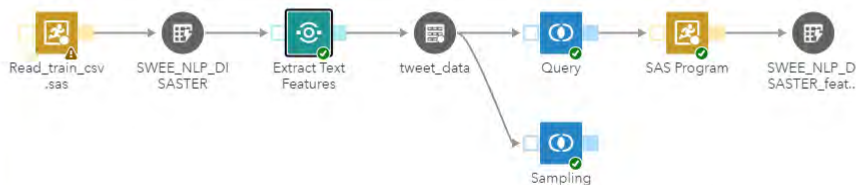
SAS Steps Shared

- Aggregate_AVG
- Aggregate_Statistics
- Anonymize and Mask Data
- Append
- Assign SAS Library
- CAS Session
- Cascading Prompts Example
- Concept_Builder_VTA
- Create Temporal KPIs
- Custom Step 3 wip
- Custom Step 3_Flags_new
- Custom_step_2_join
- CustomStep Means
- Data Builder
- Drop Promote and/or Save CAS Table
- Extract Data
- Extract Text Features**
- Get DQ Dimension
- LG_AddressVerification
- List Files
- LoqateAddressVerification
- LoqateEmailVerification
- LoqatePhoneVerification
- Match and Cluster
- Notify Teams
- Profile Table
- Promote and/or Save CAS Table
- Promote CAS Table
- Random Sample Step
- Rule Set URI
- Run Decision
- Run Python Code

Start Page Loading-Data-Feature-Extraction_snref.flw Read_train_csv.sas

Run Cancel

Flow Generated Code Submission



Sep 27, 2022, 3:33:33 PM

Extract Text Features

Base Metadata Custom RegEx Pattern Link Data Text Analytics - Start Text Analytics - Topic Creation Text Analytics - Bool R...

The additional information derived here is only available if you have SAS Visual Text Analytics licensed.

To detect the sentiment and extract text topics you have to select the language detection option.

 Do you want to use Text Analytics? (license required)

Do you want to automatically detect the text language?

 Yes No

Please select the language of your text:

English

Text Profiling

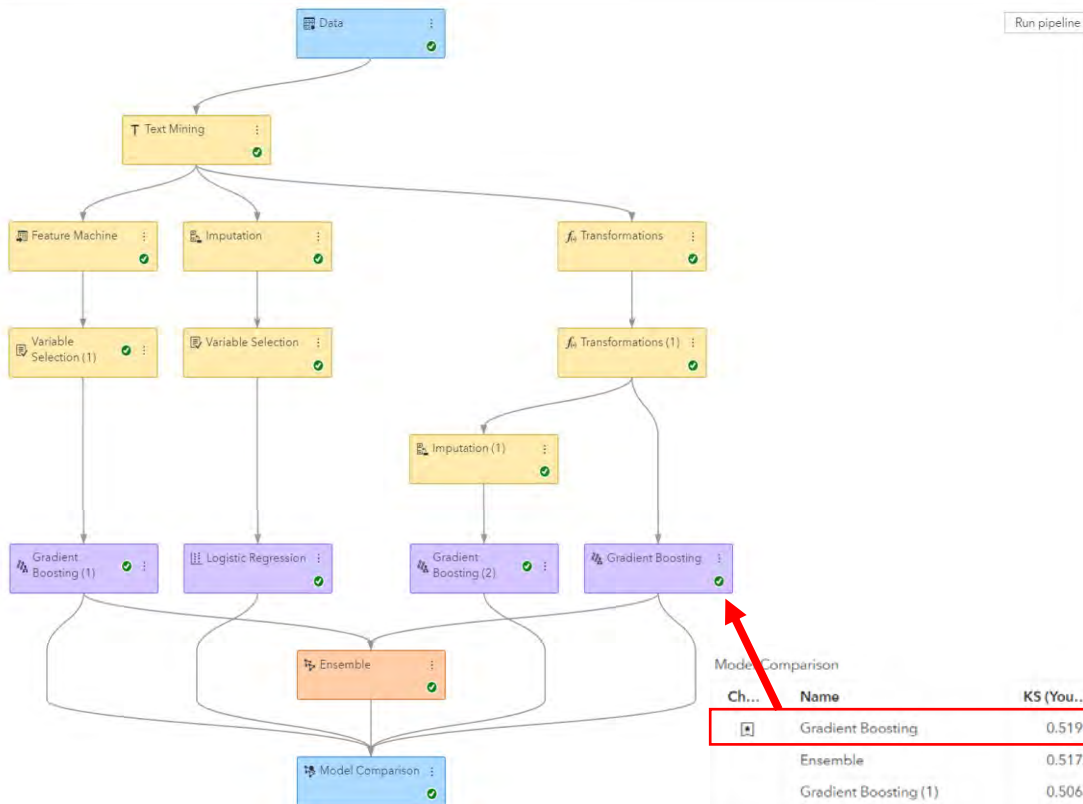
 Do you want to profile your text? Compare your text corpus to reference corpus profiles (Not available for all languages yet, raises a warning accordingly) Add Word and Sentence count per Document and Language to the Results Create a feature for the number of sentences in the Text Create a feature for the count of tokens in the longest sentence

Disaster_Prediction_MSTO

Data Pipelines Pipeline Comparison Insights

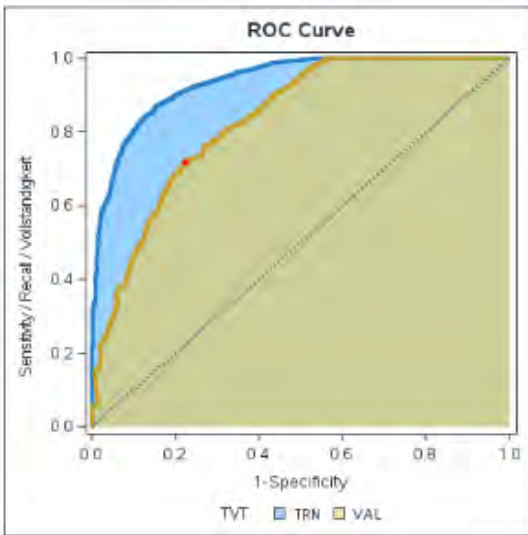
Pipeline 1 Pipeline 2 SAS Automatically Generated Pipeline : +

This pipeline was originally generated by SAS automation. The process completed successfully, but with errors. The resulting pipeline might not be the most optimal pipeline. Please check the pipeline log for more information.



Model Comparison

Ch...	Name	KS (You...	Accuracy	Averag...	Area Un...	Cumula...	Cumula...	Cutoff	Data Role
▣	Gradient Boosting	0.5191	0.7723	0.1669	0.8164	2.1762	21.7622	0.5000	VALIDATE
	Ensemble	0.5172	0.7709	0.1634	0.8221	2.1762	21.7622	0.5000	VALIDATE
	Gradient Boosting (1)	0.5063	0.7667	0.1666	0.8170	2.1868	21.8684	0.5000	VALIDATE
	Gradient Boosting (2)	0.4980	0.7630	0.1667	0.8162	2.2187	22.1868	0.5000	VALIDATE
	Logistic Regression	0.4860	0.7463	0.1742	0.8031	2.1762	21.7622	0.5000	VALIDATE



Result:

New Custom Step for SAS Studio

Creates ~550 prediction features

~ 10 feature request,

~detecting 12 bugs ,

25 commits

...btw. you'll find the relevant SAS code snippets in the notes below the slides of this slide deck

regex



Looking for Airline Flight Codes e.g. "MH370" in the twitter data.

```
data test;
set mysasfil_ ur_tweets_desaster_pred_kaegle;
run;
```

* Required Input Parameters:

```
%let ds=Text;
%let Prx=(accident|crash|lost|drug|rockn|roll|fire|flood|outbreak|big/i|/bla-
z|2.3|s|0.1|1|d|2.4|b|/|/|a-|2.3|s|0.1|1|d|2.4|b|/; *Airline Flag code z.B. MH370;
%let ID=id;
%let Text=Text;
%let MinDocCnt=10;
%let Part=PartN;
```

* Logic condition to subset for Training Data:

```
%let TRN=(PartN eq 1);
```

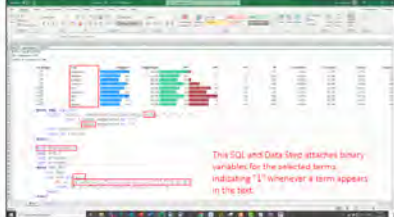
* Optional Input Parameters:

```
%let target=Target; * Required to be a numerical Binary variable with values 0 or 1;
%let MinItMeans=8;
%let MaxItMeans=2;
```

* Optional System Parameter (They must have values!!! 10 and 32 list Default):

```
%let Snippet_Window=10; * Number of characters extract before and after
Occurance;
%let Len_Occur=32;
```

BooleRule



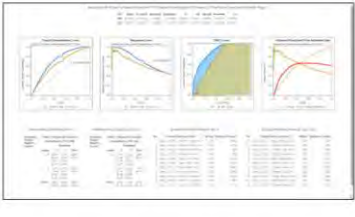
This SQL and Data file attaches binary variables for the selected terms, indicating "1" whenever a term appears in the text.

```
*BooleRule:

%macro terms(id,target,Text,loosines, Lanvace,spas,emea,mpos,mneg);
odsnois label;

*David, in order to prevent Target Leakage
(https://en.wikipedia.org/wiki/Leakage\_\(machine\_learning\))
in the Keyword and/or BooleRule Calculation we need to constrain that target
association analysis to the Training Partition only. That would require the user have
and assign a Partition Variable in its Table (if you really want to add that complication
to the flow???).
Here is my major code Modification, Use that table in the Textmine and BooleRule
actions.
HOWEVER the Features need to be generated at the end of Trn and Val data!!!! that
means on dataset k-ds;
data tmpcas.training;
set &ds.;
if PartC eq 'TRN';
run;
```

Gradboost Output



```
proc gradboost data=tmpcas.T25 ntries=70
/* Vars_ID_Try=46
LearningRate=0.35292942
SamplingRate=0.81915023
Lasso=3.99796601
Ridge=9.5148314
Number=26
MaxDepth=6*/;
partition RuleVar=PartC Train="TRN" Validate="VAL";
target target / level=nominal;
*input _stm_ ; KW: BR / level=interval;
*input &Intervall_ / level=interval;
*input &Nominal_ / level=nominal;
input _stm_ col / level=interval;
autobune tuningparameters=( samplingrate vars_to_try(omit=50)
learningrate lasso ridge) targetevent="1" objective=ks
maxtime=3600 nparallel=4;

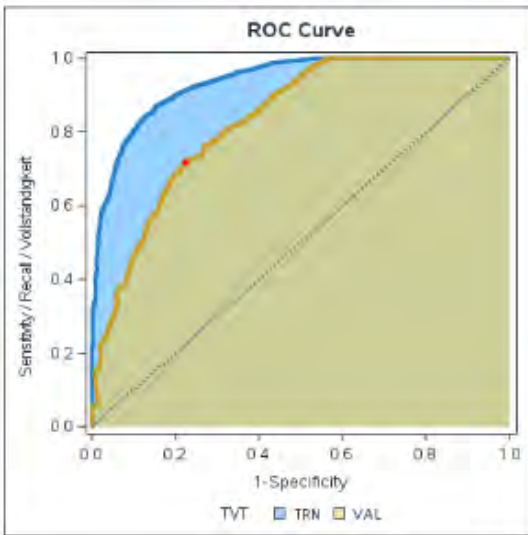
ods output TunerResults= _tempTunerResults_ ;
ods output BestConfiguration= _temp_GB_BestConfig_ ;
ods output ValidationHistory= _tempValHistory_ ;
ods output IterationHistory= _tempIterHistory_ ;
ods output FitStatistics=work.Gradboost_fit
VariableImportance=work.Gradboost_varimp;
score out=tmpcas.Scored_GB copyvars=_all_;
run;
```

sas.com



Weiterführende Literatur

- [SAS® Visual Text Analytics 8.5: User's Guide \(Viya\)](#)
- [SAS® Text Miner 14.1 Reference Help \(V9\)](#)
- [SAS® Text Analytics for Business Applications: Concept Rules for Information Extraction Models](#)
- [Git Repository von David Weik für den Text Analytics Flow \(Nutzung auf eigene Gefahr!!!\)](#)



Questions on “climbing the ROC”

Ulrich Reincke & David Weik