NIYAM IT

EFFECTIVE SOLUTIONS, MEASURABLE OUTCOMES

Predicting Disaster Declaration

Machine Learning & Predictive Analytics In Action

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What Bothered Us…

Thirty years of historical data shows that:

- On an average, it takes 20 days from the date a natural disaster occurs, to declare a *'Presidential Disaster'*
- Weather related disasters are by far the most common disaster type
- Severe and high-frequency weather alert activities correlate well with disaster activities

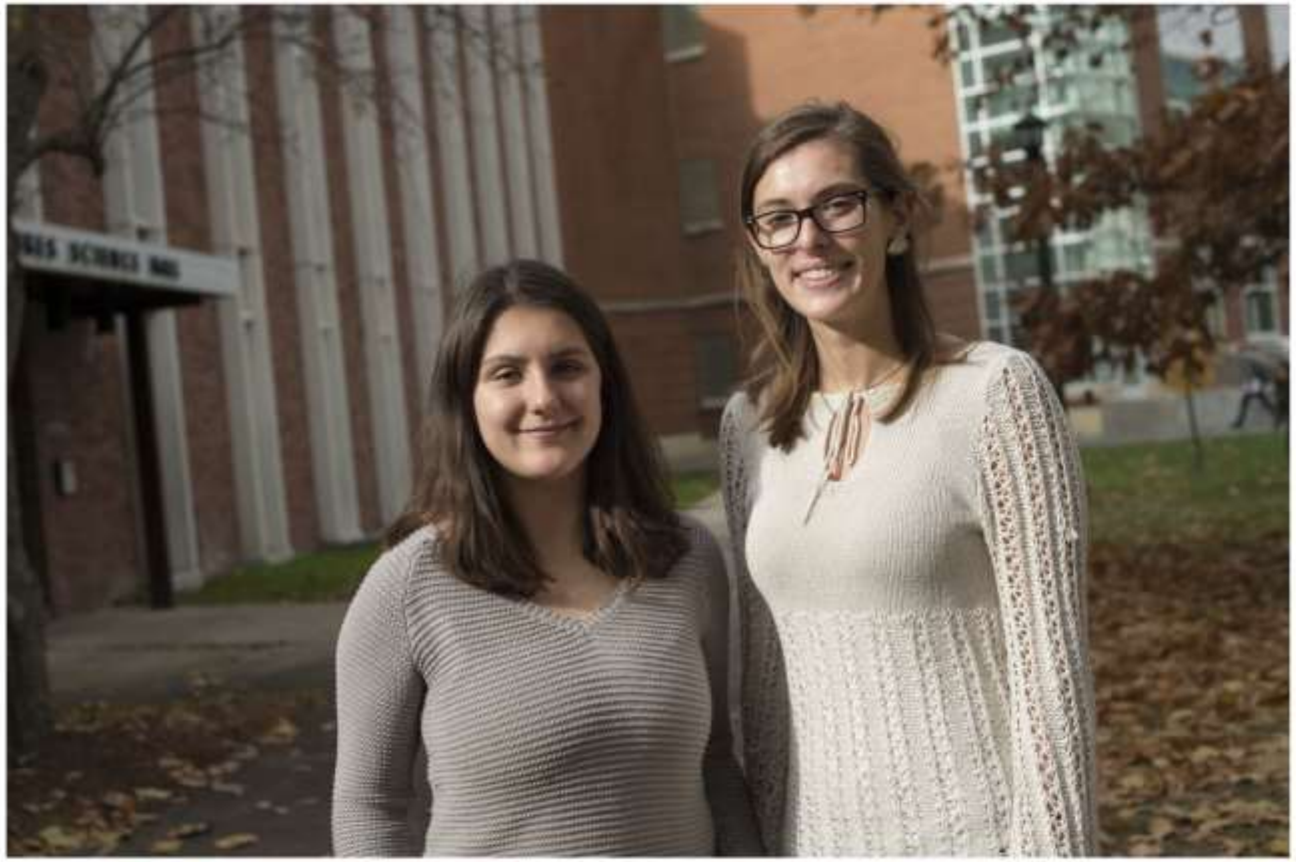
Bottom-line

- The sooner a disaster is declared, faster are the relief efforts to minimize losses and restore normalcy

The Washington Post (WP Com... (US) https://www.washingtonpost.com/local/education/two-college-seniors-got-the-election-right-when-almost-everyone-el

Visited Dropbox ReportsByQuarter # Pipeline Tracker PPP AI Active

Two college seniors got the election right when almost everyone else got it wrong



- ✓Yes, future outcomes can be predicted
- ✓One of these bright ladies is a core developer of the Predictive Tool we're going to discuss here
- ✓In Association with:

PACIFIC DISASTER CENTER

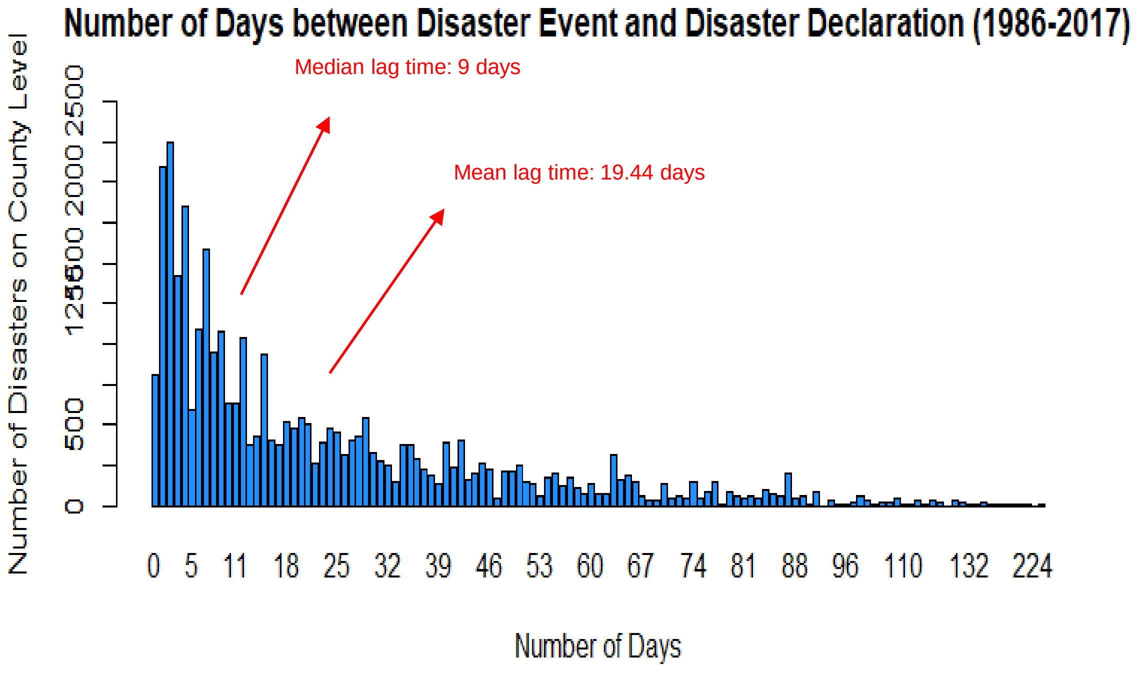
Big Data Analytics – What's Big About It?

- A few years ago a business would have gathered information, run analytics and unearthed information that could be used for future decisions…
- Today that business can identify insights for immediate decisions.
- The ability to work faster – and stay agile – gives agencies/organizations a competitive edge they didn't have before.

Machine Learning – Key Points

- Computers apply **statistical learning** (“normal distribution,” “t-distribution,” and “least squares regression”) techniques to automatically identify patterns in data.
- These techniques can be used to make highly accurate predictions.
- Identifying boundaries in data using math is the essence of statistical learning.
- More data points we have, better the predictive model can be.

Delays in Disaster Relief



FEMA Disasters as of Jan 1 2018 – June 1, 2018

FEMA Disaster #	Incident date	Declaration date	IA	PA	Lag time
DR-4370	2-Mar	8-Jun	No	No	98
DR-4371	13-Mar	8-Jun	No	No	87
DR-4368	6-Mar	8-Jun	No	No	94
DR-4367	2-Mar	30-May	No	No	89
DR-4364	15-Apr	8-May	Yes	No	23
DR-4363	14-Feb	4-May	Yes	No	79
DR-4362	19-Mar	26-Apr	Yes	No	38
DR-4361	21-Feb	26-Apr	No	No	64
DR-4359	14-Feb	17-Apr	No	No	62
DR-4360	14-Feb	17-Apr	No	No	62
Dr-4358	9-Feb	12-Apr	No	No	62

June 15, 2018 – Ellicott City, MD, awaiting for Disaster Declaration. Actual flooding happened on May 26th.

Increase in Vulnerability

It's more important now to be prepared for a disaster:

- Climate change – Record breaking weather phenomena occurs too frequently.
- Topography change – Increased urbanization (a.k.a concretization) causes changes or hinders water runoff patterns and absorption.
- Increasing population – the stakes are higher now.
- BTW: Flood is still the number one peril in the USA.

How Data Analytics Can Help

1. Significant amount of alert data comes in from multiple sources related to natural disasters (over 50,000 per month from NOAA/NWS) affecting the entire country.

2. A customized watch-area can be established by specifying the geographic location, alert type, severity and certainty. This pin-points the area to focus on, as the weather event unfolds.

3. NOAAs incoming weather alerts (every 4 hrs.), can be analyzed and applied to a predictive modeling technique to indicate the probability of a disaster declaration and quantify the impacts of the disaster.

4. Near real time generation of disaster probabilities can reduce the lag time between the actual weather event and disaster declaration.

Let’s Get Started – Build A Tool That Can Predict Disaster Declaration Real Time Basis

Step #1 – Input Data

- FEMA’s List of Declared Disasters (1986-present):
    - Contains event begin and end dates, declaration date, County FIPS6, program declared, disaster type, etc.
    - Declared on county/parish level
    - Each disaster is uniquely defined by ID and county FIPS6
    - Public Assistance (PA) and Individual Assistance (IA) program impacts
- NOAA’s Weather Alerts (1986-present):
    - Contains alert begin and end dates, alert type, alert level (warning, watch, advisory, outlook, statement), County FIPS6
    - Declared on county/parish level
- Census, Social Vulnerability Index, Geographic Vulnerability Index, Hazus decile ratings

Let’s Get Started (cont’d)

Step #2: Identifying the right Impact Vectors

Our predictive model takes into account these impact vectors:

- **Dominant Alert** – The incoming raw data feed contains multiple alerts of different event types, resulting from a single weather phenomenon. Our algorithms eliminate white noise and establish dominant alerts at a given time and place.

- **Population and urbanization levels at zip code levels**, to evaluate the possible impact of a disaster.

- **Hazus Decile ratings** – Areas with high ratings have higher probability of disasters.

- **Social Vulnerability Index (SoVi)** – Areas with high SoVi ratings have higher probability of disasters.

How Our Tool Works – Alert Viewer

1. **Real time raw weather data NOAA/NWS collected every 4 hours:**

- NOAA weather alerts provide near-real time inputs on the weather as it happens.
- We use this rich and reliable information as an important vector to predict a disaster map.

2. **Alerts processing:**

- Raw data from NOAA weather alerts contains duplicates, blanks and expired alerts.
- The ‘Data Clean up’ process removes duplicates, fixes missing data and tags the expired alerts.

3. **Establishing Alert Dominance:**

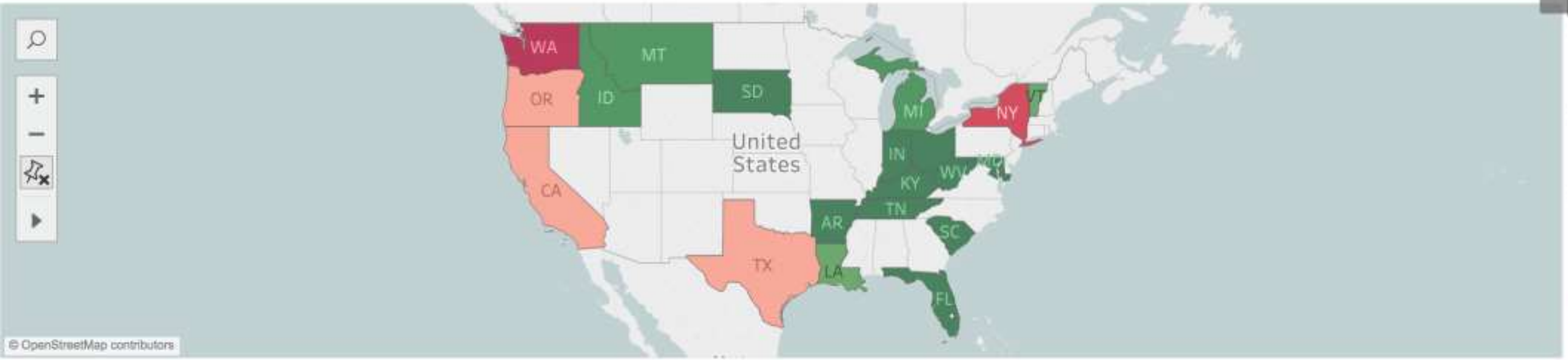
- Our algorithm ranks the incoming alerts based on the severity, past occurrences and urgency to establish the most dominant alerts.

4. **Active Weather Alerts:**

- The resulting data set, is a clean aggregated view of severe weather events happening in real time.
- This data set can be refreshed right after NOAA releases the next set of alerts, roughly after 4 hours.

Alert Viewer - Active NOAA Alerts

States with Active Alerts (updated as of 9/5/2017)



Select Severity
(All)

Select Event
(All)

Select Certainty
(All)

Select Urgency
(All)

Number of Active Alerts
10.0 596.0

Severity
- Severe
- Moderate
- Minor
- Unknown

Key Statistics

Number of Alerts by Event Type

AK	High Wind Watch	14
	Special Weather Stateme..	40
AR	Flood Warning	18
CA	Air Quality Alert	310
	Dense Smoke Advisory	23
	Fire Weather Watch	12
FL	Flood Warning	59
HI	Wind Advisory	28
ID	Air Quality Alert	74
	Red Flag Warning	38
IN	Beach Hazards Statement	50
KY	Flood Warning	38

Effective from:

AK	09/04/2017 22:49:00
AR	09/04/2017 19:49:00
CA	09/04/2017 20:43:00
FL	09/04/2017 22:00:00
HI	09/04/2017 15:28:00
ID	09/04/2017 14:14:00
IN	09/05/2017 04:41:00
KY	09/05/2017 04:34:00
LA	09/04/2017 21:49:00
MD	09/04/2017 20:07:00
MI	09/05/2017 04:11:00
MT	09/04/2017 09:00:00

Alert Viewer – Filter Criteria

Select Severity

(All)

- [x] (All)
- [x] Minor
- [x] Moderate
- [x] Severe
- [x] Unknown

Cancel Apply

Select Event

(All)

Enter search text

- [x] (All)
- [x] Air Quality Alert
- [x] Beach Hazards Statement
- [x] Coastal Flood Advisory
- [x] Dense Smoke Advisory
- [x] Extreme Fire Danger
- [x] Fire Weather Watch
- [x] Flood Warning
- [x] Heat Advisory
- [x] High Wind Watch
- [x] Hurricane Warning
- [x] Red Flag Warning
- [x] Rip Current Statement
- [x] Special Weather Statement
- [x] Wind Advisory

Cancel Apply

Select Urgency

(All)

- [x] (All)
- [x] Expected
- [x] Future
- [x] Unknown

Cancel Apply

Select Certainty

(All)

- [x] (All)
- [x] Likely
- [x] Observed
- [x] Possible
- [x] Unknown

Cancel Apply

Alert Viewer – Alerts by Event Types

Key Statistics

Number of Alerts by Event Type

Calhoun County	Flood Warning	6
Chambers County	Flood Warning	10
Colorado County	Flood Warning	2
DeWitt County	Flood Warning	2
Fort Bend County	Flood Warning	26
Galveston County	Air Quality Alert	16
	Flood Warning	1
Goliad County	Flood Warning	1
Grimes County	Flood Warning	2
Hardin County	Flood Warning	11
Harris County	Flood Warning	128
Jackson County	Flood Warning	1
Jasper County	Flood Warning	7

Effective from:

Austin County	09/04/2017 20:32:00
Brazoria County	09/01/2017 11:23:00
Brazos County	09/04/2017 20:32:00
Calhoun County	09/04/2017 20:30:00
Chambers County	09/04/2017 21:13:00
Colorado County	09/04/2017 20:32:00
DeWitt County	09/04/2017 20:30:00
Fort Bend County	09/04/2017 21:13:00
Galveston County	09/04/2017 21:13:00
Goliad County	09/04/2017 20:30:00
Grimes County	09/04/2017 21:13:00
Hardin County	09/04/2017 20:38:00

How our tool works

4. Visualizations:

Active Alerts: The resulting active weather alerts dataset is visualized in an intuitive Tableau dashboard that displays all currently active alerts on a map. It offers a drill down view of the impacted counties, for the specific weather event selected. Users can set location preferences, weather event preferences and watchlist of high severity alerts.

Predicted Disaster Map: For all locations in the active alerts dataset, 'probability of disaster' is generated by our proprietary predictive analytics model. The predicted disaster map shows counties and their corresponding probability of being declared as IA, PA or NFIP disasters as influenced by the current weather conditions.
Based on the magnitude of current probability, population impacted and volume of past payouts, an estimated payout amount is generated.

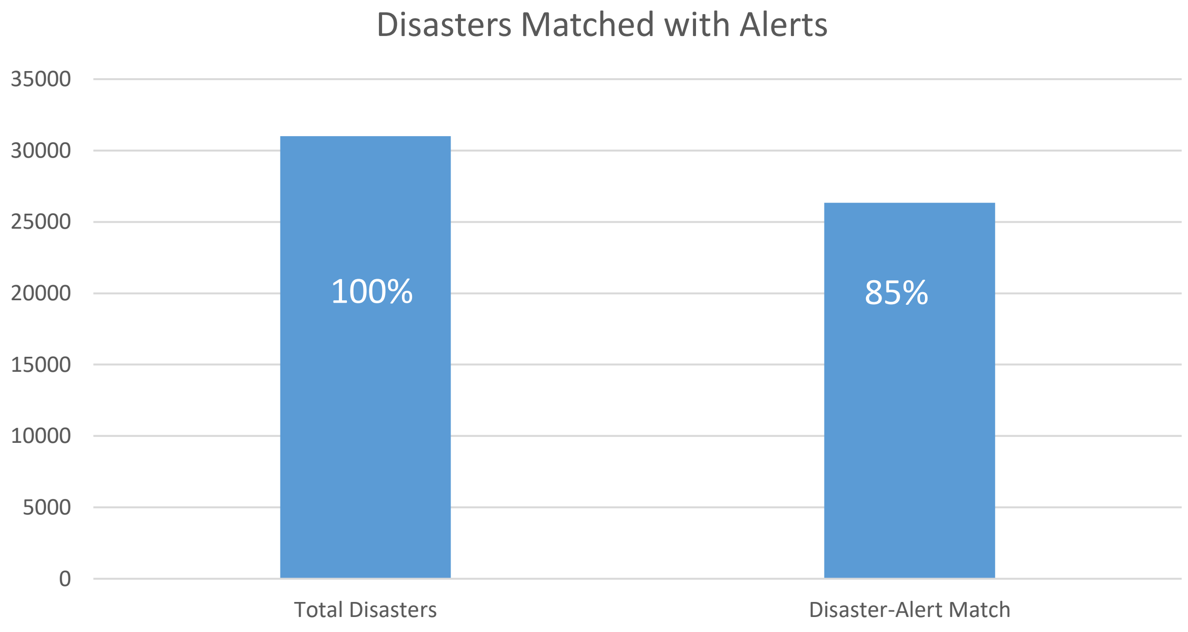
How Our Predictive Analysis Tool Works

The Analytics core : Establishing the Disaster-Alert Correlation

Utilizing powerful R functions, we aggregated the ingested data and discovered correlations between weather alerts and disaster declarations.

- 100% of unique disaster IDs were matched with at least one alert.

- 85% of unique disaster IDs on county level were matched with at least one alert.



How Our Predictive Analysis Tool Works (cont'd)

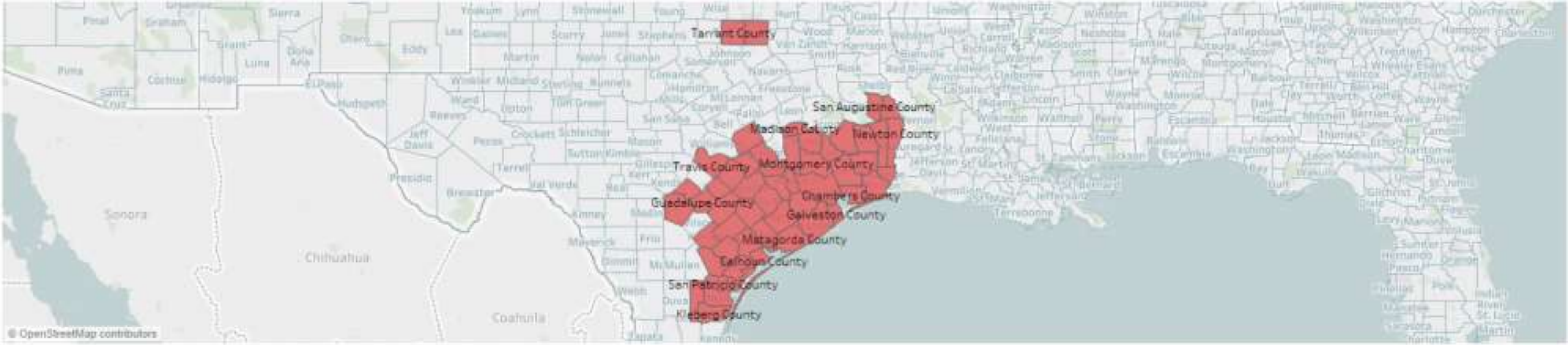
- When current weather alerts and user specified locations are input to the model, it generates forecasts/probability of disaster declarations.
- Applying more statistical modeling techniques to past relief efforts it was possible to quantify the estimated disaster relief funding amounts.
- The predicted disaster map shows counties and their corresponding probability of being declared as IA, PA or NFIP disasters as influenced by the current weather conditions.
- Based on the magnitude of current probability, population impacted and volume of past payouts, an estimated payout amount is generated.

How It Looks – IA/PA/ NFIP Probabilities

Weather Alerts PoC

Weather Alerts | Predictions | Start Over

Predictions for TX (updated as of 9/5/2017)



Select Probability Range

(All)

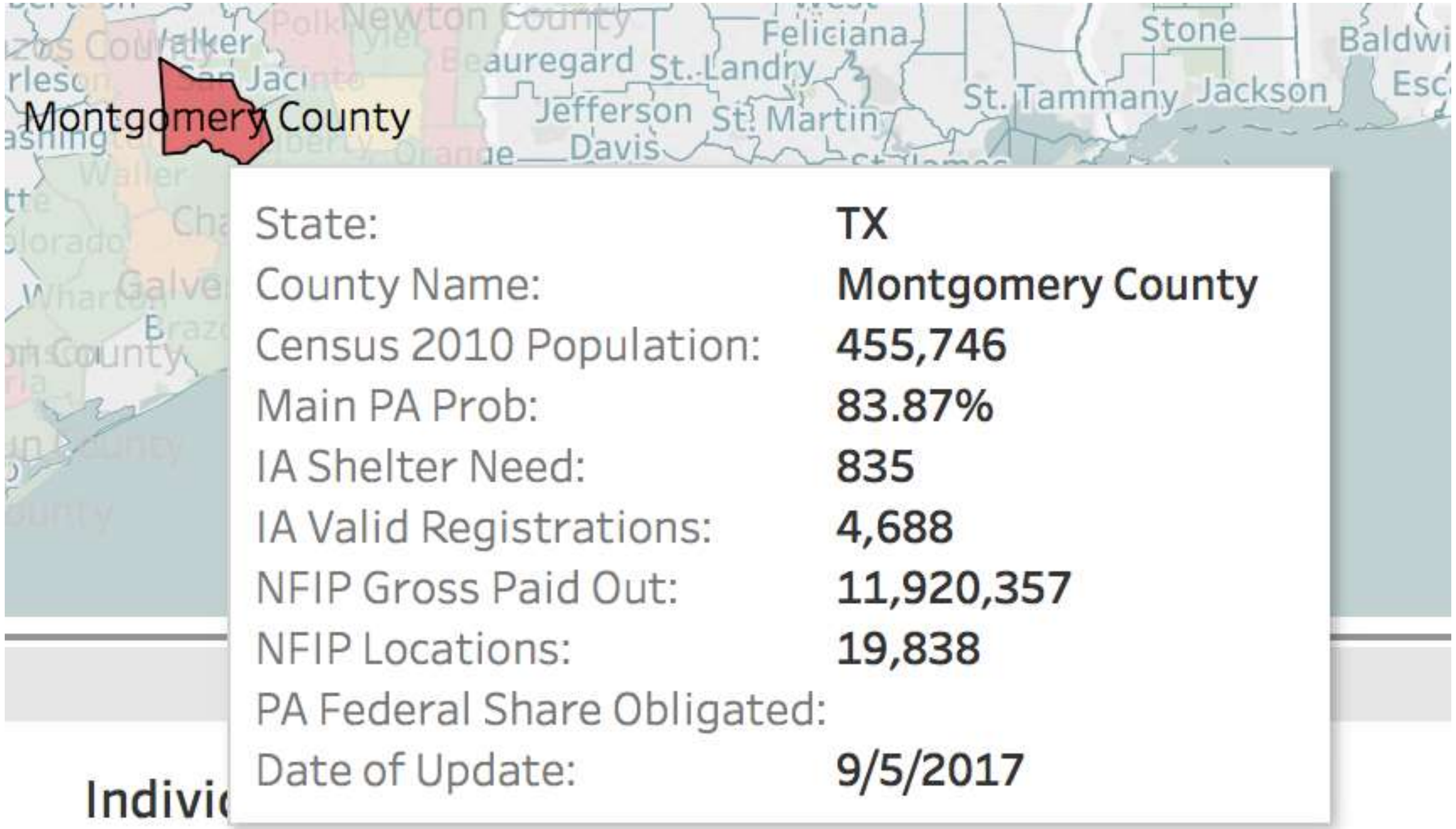
Probability

70.01 - 100

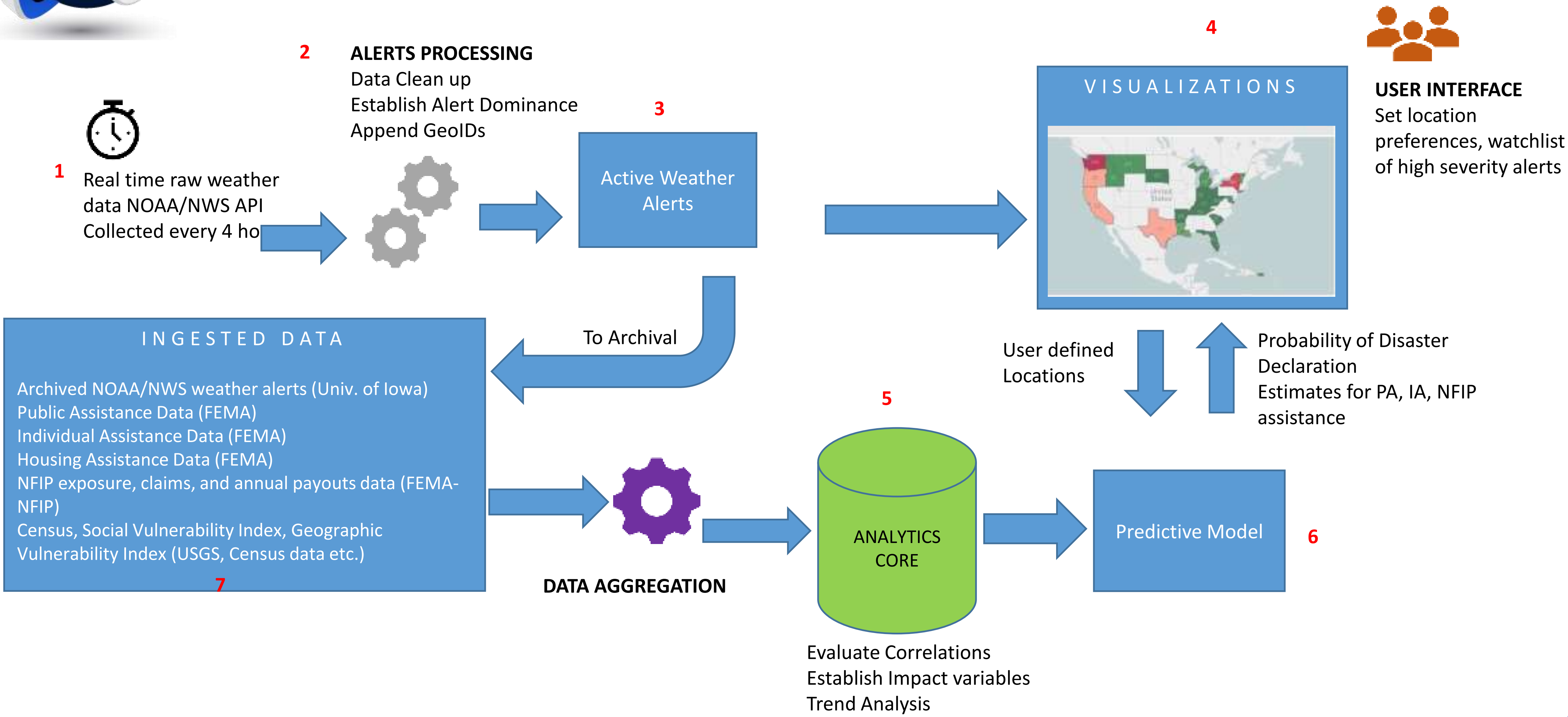
County Probabilities of Presidential Disasters

Demographics		Public Assistance		Individual Assistance			NFIP		
County Name	Population	PA Probability	Federal Share Obligated	IA Probability	Valid Registrations	IA Shelter Need	NFIP Probability	No. of Locations	Gross Paid
Caldwell County	38,066	95.71%		85.71%			90.71%		
Calhoun County	21,381	95.73%		85.73%			90.73%		
Chambers County	35,096	95.91%		85.91%			90.91%		
Colorado County	20,874	96.15%		86.15%	99	23	91.15%		
Comal County	108,472	96.20%		51.20%			61.20%		
Dallas County	2,368,139	96.34%		51.34%			61.34%		
DeWitt County	20,097	96.42%	$405,000.00	86.42%			91.42%		
Fayette County	24,554	96.65%		86.65%			91.65%		
Fort Bend County	585,375	96.73%		86.73%	2,058	653	91.73%	33,386	$30,330,504.07
Galveston County	291,309	96.80%	$2,722,302.00	86.80%			91.80%	55,965	$22,315,976.27
Goliad County	7,210	96.90%		86.90%			91.90%		
Gonzales County	19,807	96.91%		86.91%			91.91%		
Grimes County	26,604	97.02%		87.02%	653	79	92.02%		
Guadalupe Coun..	131,533	97.03%		52.03%			62.03%		
Hardin County	54,635	97.19%		87.19%			92.19%		
Harris County	4,092,459	97.20%	$92,190,465.54	87.20%	22,014	3,497	92.20%	240,600	$152,540,503.72
Jackson County	14,075	97.54%		52.54%			62.54%		

How It Looks – IA/PA/ NFIP Probabilities



How Our Tool Works



More Value Adds: Analytics & Machine Learning

- By incorporating continuous feedback of success rate of the model, it can be fine tuned to achieve higher accuracy.

- The probability patterns can be programmed into automated machine learning scripts that indicate disaster probabilities on ingestion of weather alerts, without user intervention.

- Additional data sources and loss estimation methodologies can be integrated with the model to generate what-if scenarios in domains like **agriculture, supply chain logistics, impacts on public utilities and essential services**.

Next Steps

- This is still in Pilot Stage.
- Working with DHS S&T, FEMA to scale it to Production Level.
- Work with State and Local Officials to enhance the tool further.

Thank You

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