

Panel : Value Proposition for Big Data Analytics

Topic Overview:

Mladen Kezunovic, Coordinator/Moderator

Texas A&M University

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Panel : Value Proposition for Big Data Analytics

- ***Chair, Introduction and overview:*** *Mladen Kezunovic*, Director, Smart Grid Center, Texas A&M University
- ***Utility Use Cases:*** Doug Dorr, Program Manager, EPRI
- ***Future and visualization:*** Mark Johnson, Managing Director, Utility Analytics Institute
- ***Vendors' perspective:*** Mahesh Sudhakaran, Chief Digital Officer, IBM Energy and Utility business
- ***Regulatory ,Legal Issues & Consumer Advocate views:*** Chris Ayers (substitute for David Colata)



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Outline

Expectations

Big Data vs. Big Data Analytics

Big Data Properties

Data Science

Big Data Processing Infrastructure

Example: Predicting outages

Panel Introduction:

- Panelist
- Questions

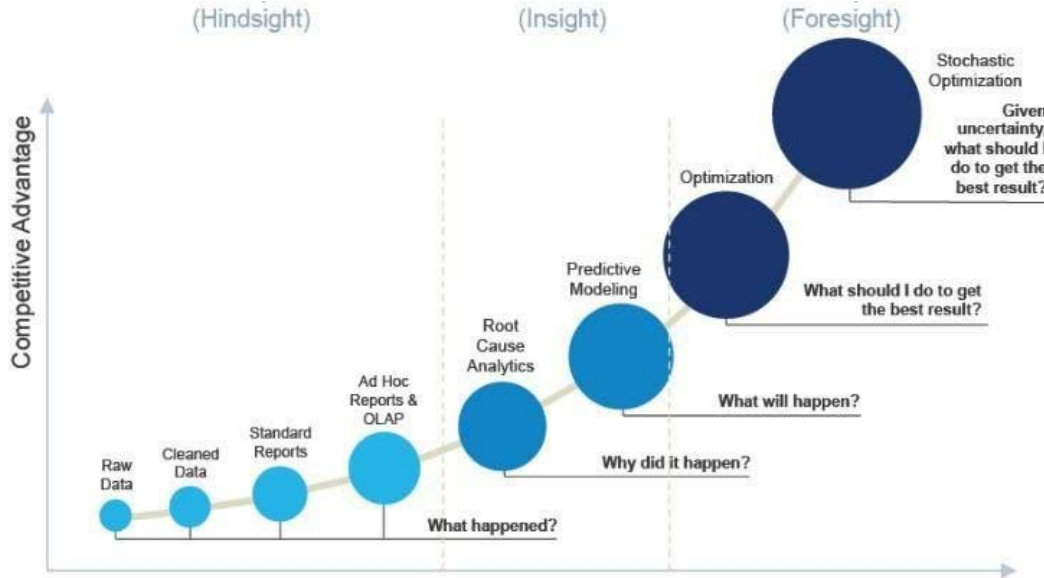


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Expectations

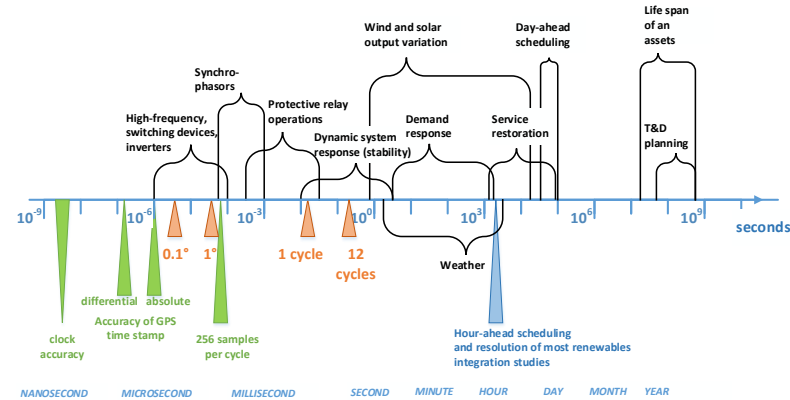
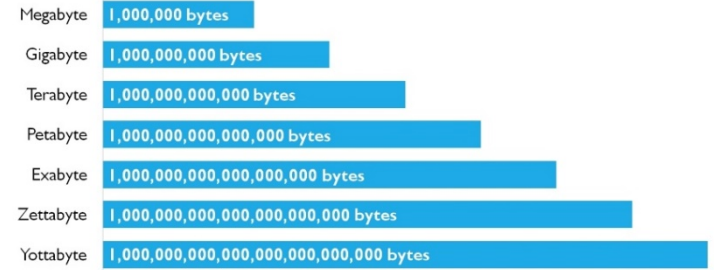


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Big Data Properties

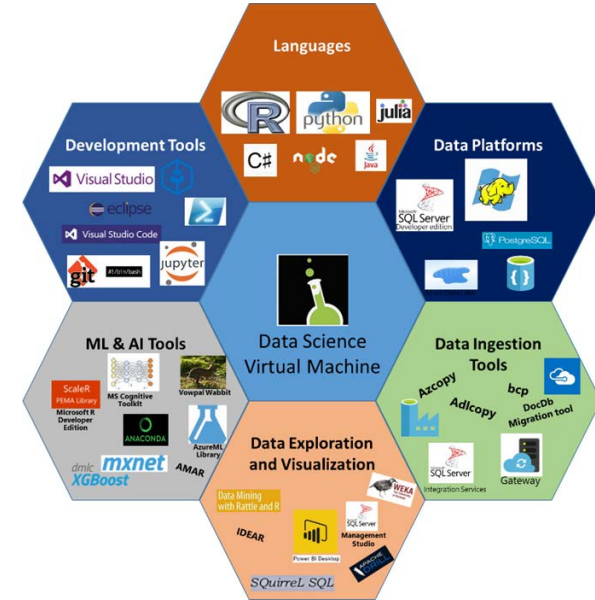
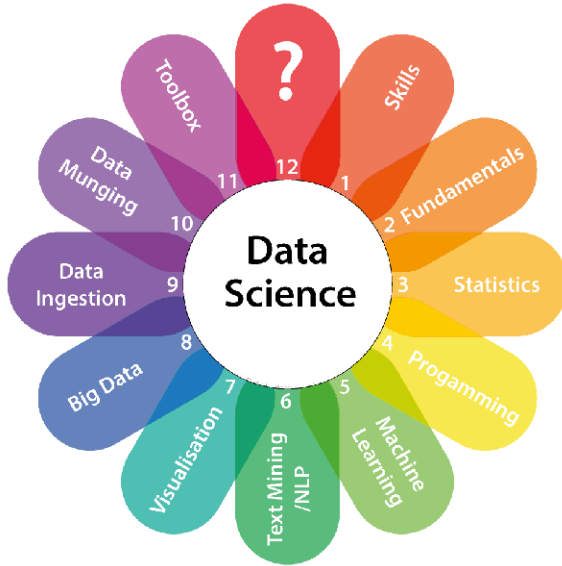


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Data Science & Processing Infrastructure



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T&D Outage Prediction

Example:

Big Data Analytics



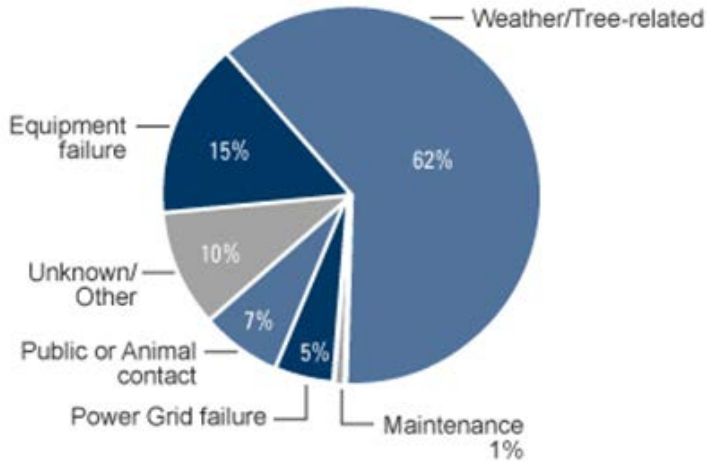
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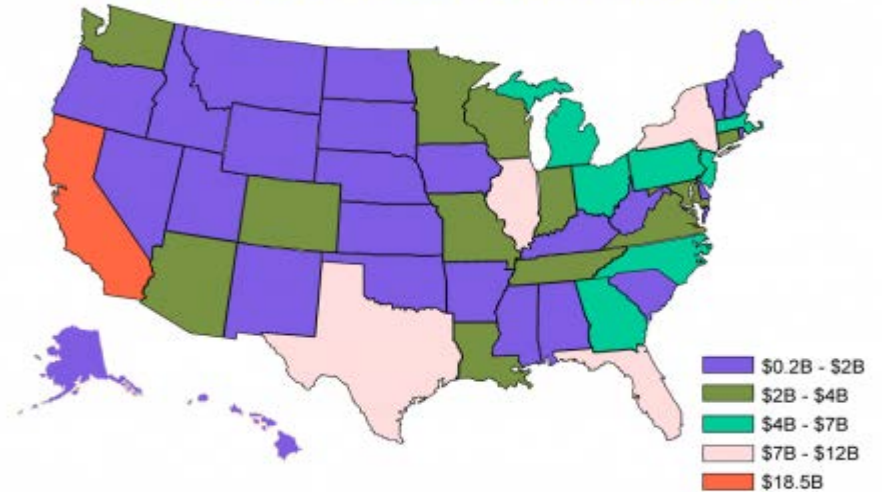
Example: outages

Major causes of power outages in the U.S.



Annual Business Losses from Grid Problems

Primen Study: \$150B annually for power outages and quality issues



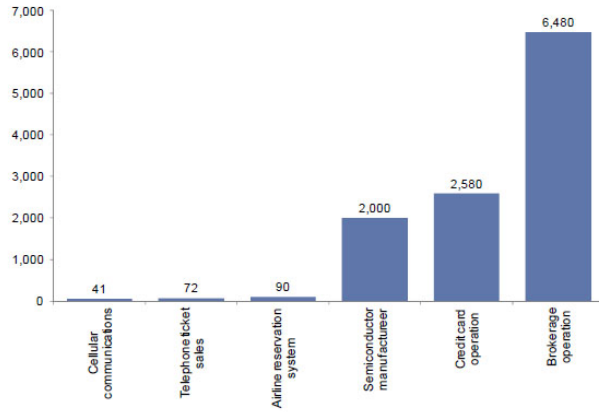
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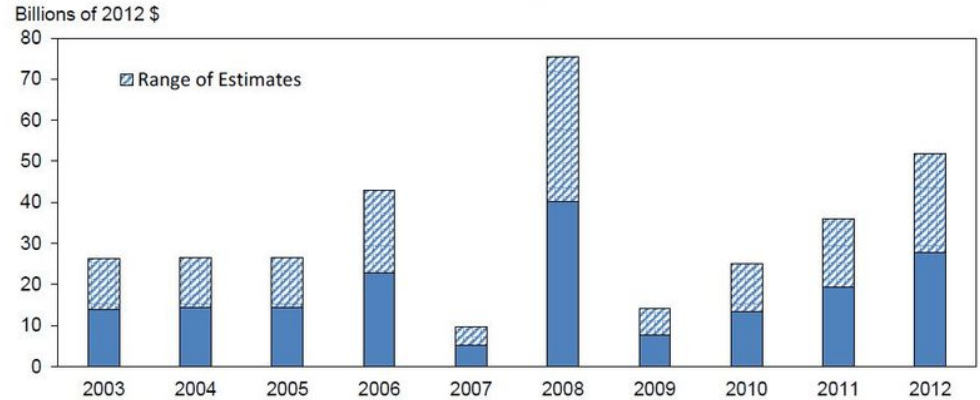
Cost

The real victim of power outages are businesses in general
 US\$'000 (2010); average cost of one hour power interruption in the US
 per type of customer



Source: US Department of Energy.

Estimated Costs of Weather-Related Power Outages



Source: CEA estimates using data from Census Bureau, Department of Energy, Energy Information Administration, Sullivan et al 2009.



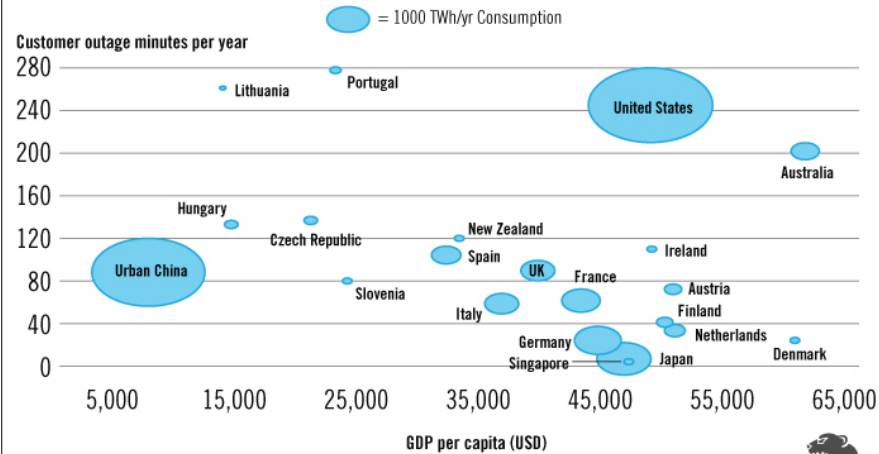
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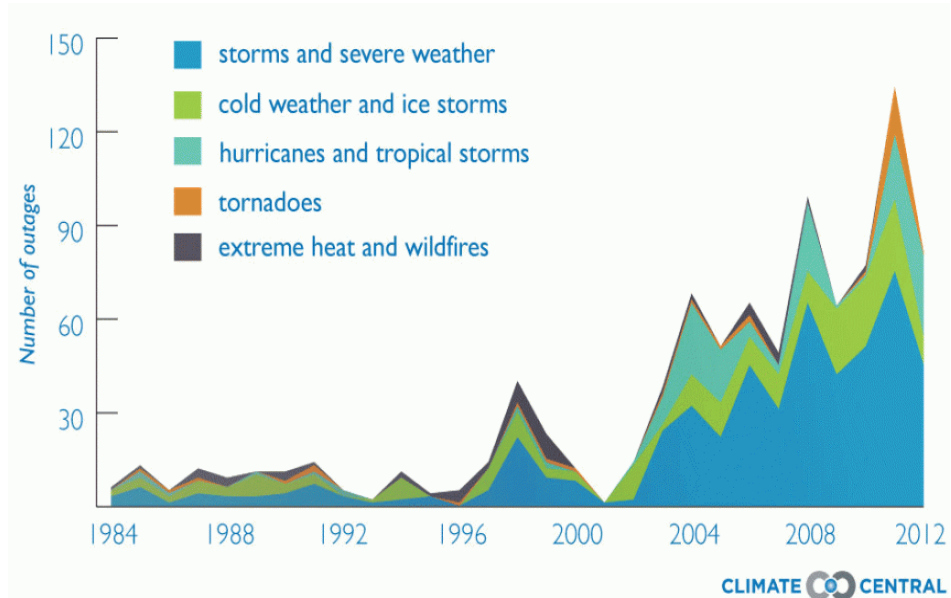
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Impact

International Electricity Grid Reliability



Source: The Brattle Group, Galvin Power Institute, Council of European Energy Regulators, China Southern Power Grid



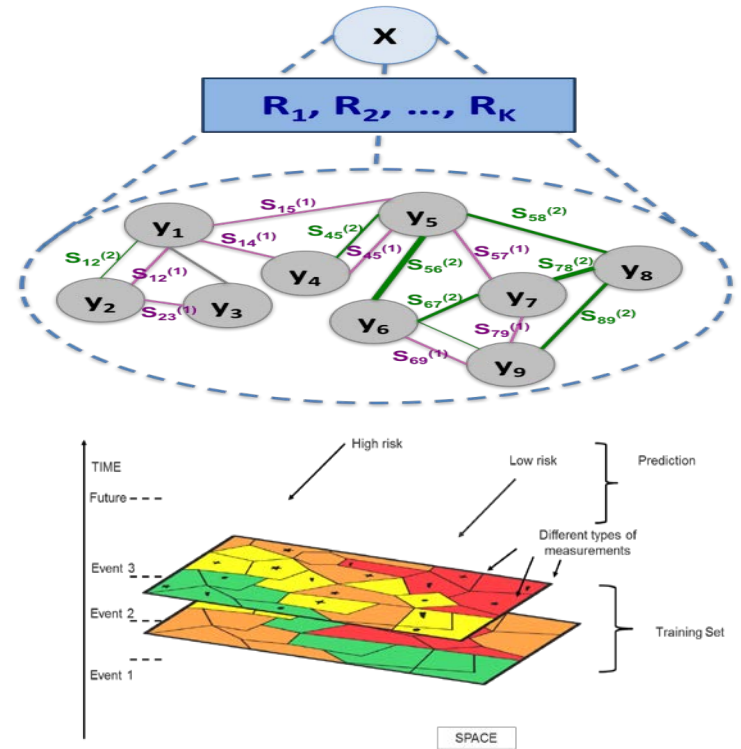
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Predictive Data Analytics

Smart Grids Big Data



M. Kezunovic, Z. Obradovic, T. Dokic, B. Zhang, J. Stojanovic, P. Dehghanian, and P. -C. Chen, "Predicating Spatiotemporal Impacts of Weather on Power Systems using Big Data Science," Springer Verlag, Data Science and Big Data: An Environment of Computational Intelligence, Pedrycz, Witold, Chen, Shyi-Ming (Eds.), ISBN 978-3-319-53474-9, 2017.

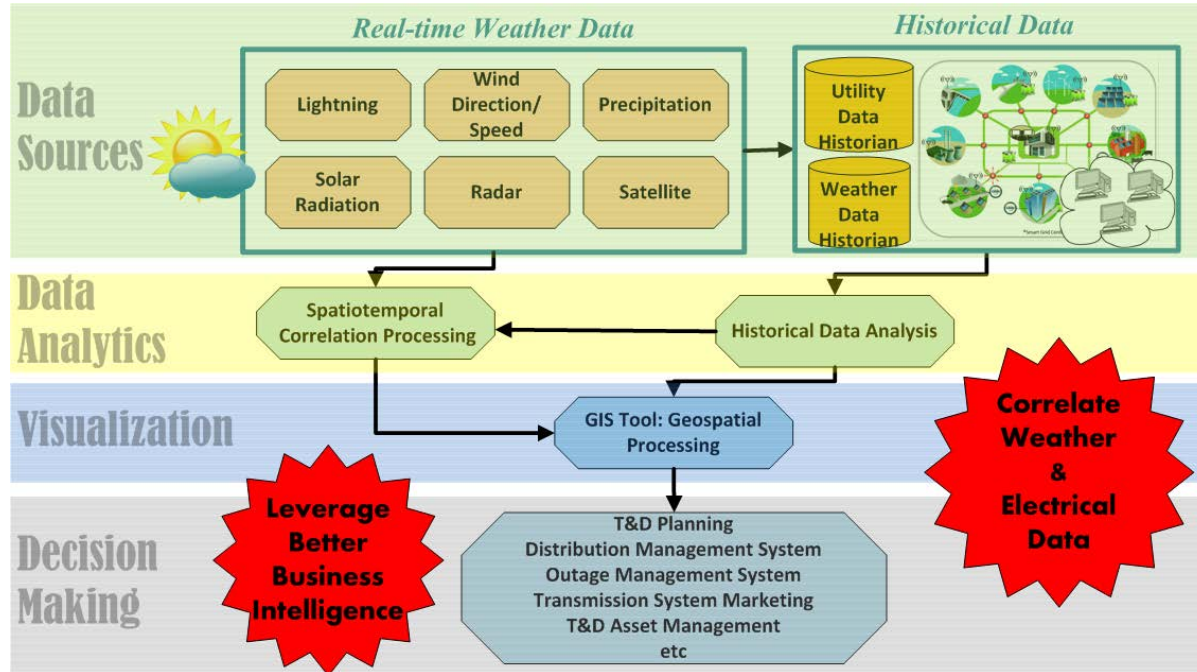


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BD for Risk Assessment

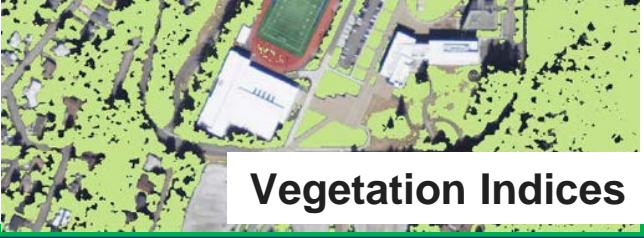
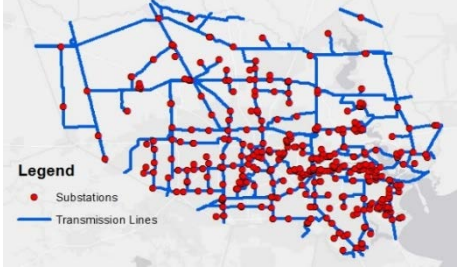
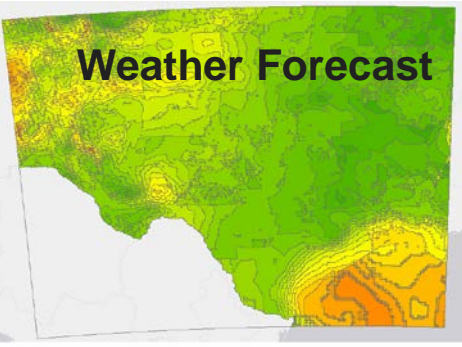
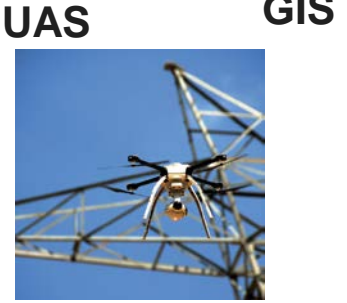
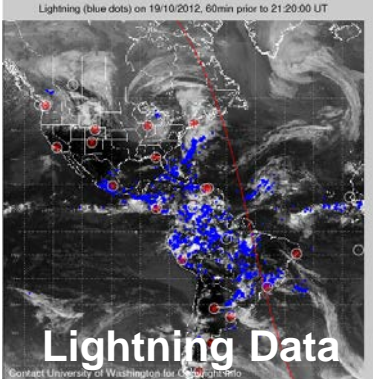
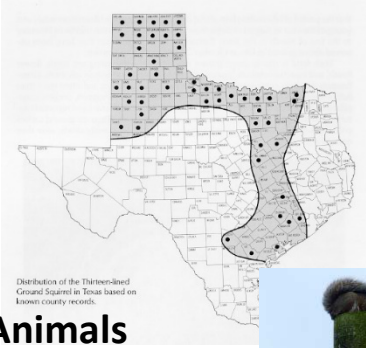
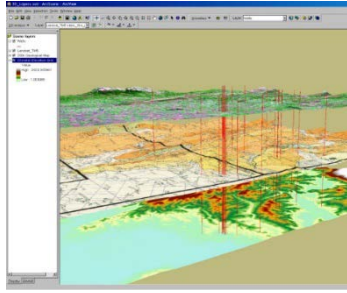


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BD Data Aggregation



BD Data Properties

			VELOCITY		VOLUME	
	Source	Data Type	Temporal Resolution	Spatial Resolution	Measurements	
V	Automated Surface Observing System	Land-Based	1 min	900 stations	Air Temperature, Dew Point, Relative Humidity, Wind Direction, Speed and Gust, Altimeter, Sea Level Pressure, Precipitation, Visibility...	
V	Level-2 Next Generation Weather Radar	Radar Data	5 min	160 high-resolution Doppler radar sites	Precipitation and Atmospheric Movement	
A	NOAA Satellite Database	Satellite Data	Hourly, daily, monthly	4 km	cloud coverage, hydrological observations (precipitation, cloud liquid water, total precipitable water, snow cover...), pollution monitoring...	
R	Vaisala U.S. National Lightning Detection Network	Lightning Data	Instantaneous	Median Location Accuracy 200-500m	Date and Time, Latitude and Longitude, Peak amplitude, Polarity, Type of event: Cloud or Cloud to Ground	
I	National Digital Forecast Database	Weather Forecast Data	3 hours	5 km	Wind Speed, Direction, and Gust, Relative Humidity, Convective Hazard Outlook, Tornado Probability, Probability of Thunderstorms...	
E	Texas Parks & Wildlife Department	Texas Ecological Mapping Systems Data	static	10 m	Distribution of different tree species	
E	Texas Natural Resources Information System	NAIP	year	50 cm – 1 m	High Resolution Imagery	
T	National Aeronautics and Space Administration	3D Global Vegetation Map	static	1 km	Canopy height data	
Y	National Cooperative Soil Survey	gSSURGO	static	10 m	Soil type	
	Utility	Historical Outage Data	instantaneous	Feeder section	Location, start and end time and date, number of customers affected, cause code	
		Tree Trimming Data	day	Feeder	Feeder location, date, trimming period, number of customers affected, cost of trimming	
		Network GIS data	static	Infinity (shapefile)	Poles: location, material/class, height Feeders: location; conductor size, count, and material; nominal voltage	
		Historical Maintenance Data	day	Tower location	Start and end date and time, location, type (maintenance, replacement), cost, number of customers affected	
		Insulator asset data	static	Infinity (shapefile)	Surge Impedances of Towers and Ground Wires, Footing Resistance, Component BIL	
		In-field measurements	instantaneous	Tower location	Leakage Current Magnitude, Flashover Voltage, Electric Field Distribution, Corona Discharge Detection, Infrared Reflection Thermography, Visual Inspection Reports	

	Data Class	Data Source (Measurements)	VOLUME (Data file size)	VELOCITY (Rate of use)	VERACITY (Accuracy)
V	Utility measurements	SM	120GB per day/ device	Every 5-15 min	error <2.5%
A		PMU	30GB per day/device	240 samples/sec	error <1%
R		ICM	5GB per day/device	250 samples/sec	error <1%
E		DFR	10MB per fault/device	1600 samples/sec	error <0.2%
R	Weather data	Radar [27]	612 MB/day per radar	Every 4-10 min	1-2 dB; m s ⁻¹
I		Satellite [28]	At least 10 GB per day	Every 1-15 min	VIS<2%; IR<1-2K
E		ASOS [29]	10 MB/day per station	Every 1 min	T-1.8°F, P<1%, Wind speed - 5%, RR - 4%
T		NLDN [30]	40 MB/day	During lightning	SE < 200m, PCE <15%
Y		NDFD [31]	5-10 GB/day per model	1 - 12 hours	Varies by parameter
	Vegetation and Topography	TPWD EMST [32]	2.7 GB for Texas	static	SE < 10 m
		TNRIS [33]	300 GB for Texas	static	SE < 1 m
		LIDAR [34]	7 GB for Harris Co.	static	HE < 1m, VE < 150 cm



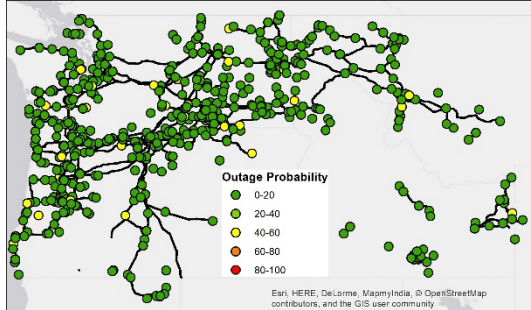
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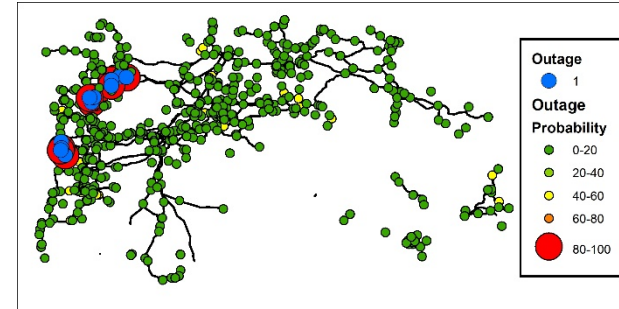
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BD Analytics Outcomes

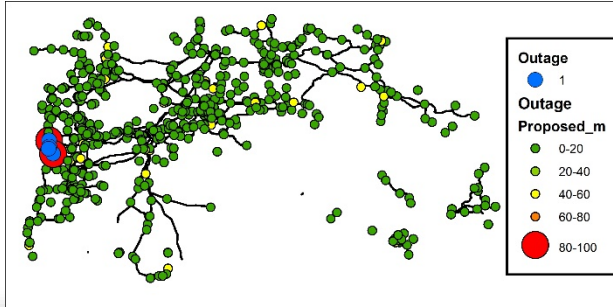
Probabilities of outages for no outage



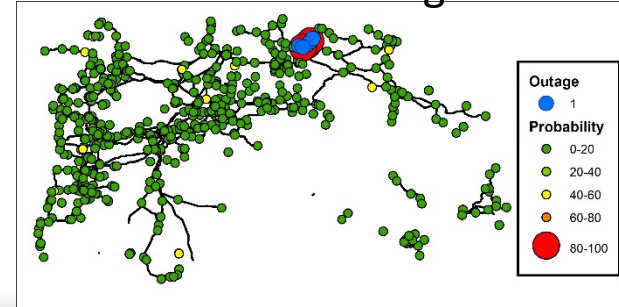
Probabilities of outages for lightning



Probabilities of outages for vegetation



Probabilities of outages for ice



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Takeaways

- Extensive research is needed to bring BD Analytics into utility practice:
 - Data analytics has been used in the power system domain for over 50 years, but Big Data Analytics is in its infancy
 - The Big Data Applications require intensive and costly effort to prepare the data (ingestion, cleansing, curation)
 - The gap between the Big Data platforms and utility legacy software (EMS, DMS, MMS) uses is huge, and costly
 - Utility predictive methods do not explore data sciences advances (Deep learning, spatiotemporal scaling, etc.)
- The government contribution may be in the following areas:
 - Make government sources of data readily useable
 - Fund research in new applications of Big Data Analytics
 - Help industry demonstrate the new business opportunities
 - Explore benefits of predictive methods in solving grand challenges

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Panel Questions

Use Cases: What is the state of the art in Big Data Analytics products and R&D developments suitable for power industry applications?

Barriers and gaps: What prevents faster development and deployment of the solutions that utilize Big Data Analytics? Is there a compelling business case (value) for the stakeholders (utilities, ISO's, Load Serving Entities, third party aggregators, data providers) to adopt Big-Data Analytics? What is this business case?

Customer role and needs: How to access data related to energy consumption that resides at the customer site or is collected at the points of customers interfacing to the grid? How to distribute data and knowledge to end-use customers in a manner that facilitates decisions?

Regulatory and legislative framework: How does such framework shape crucial issues in data access such as cybersecurity, privacy, data ownership, critical infrastructure confidentiality, data as service?



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