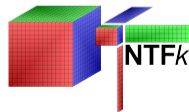
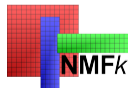
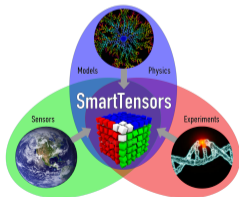


Unsupervised and Physics-Informed Machine learning in Geosciences

Velimir V. Vesselinov (monty) (vvv@lanl.gov)

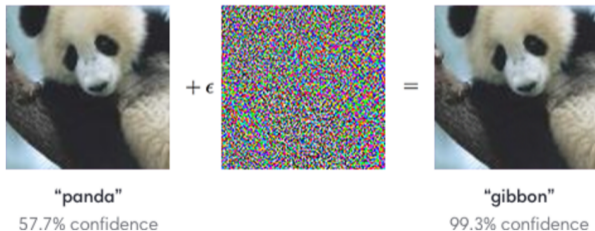
Earth and Environmental Sciences Division, Los Alamos National Laboratory, NM, USA

<http://tensors.lanl.gov>



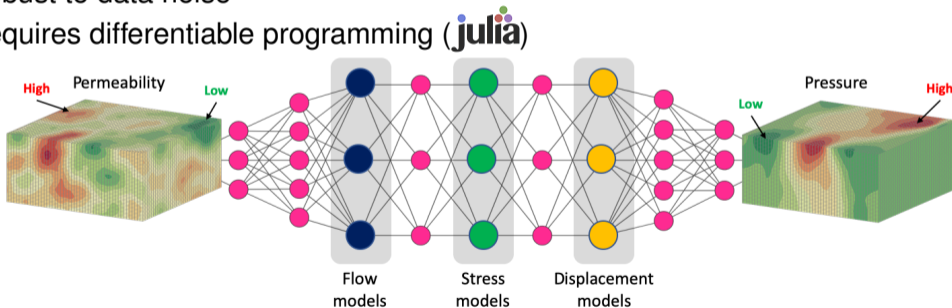
- ▶ **Supervised** ML
- ▶ **Physics-informed** ML
- ▶ **Unsupervised** ML

- ▶ **Supervised** ML: learns everything from data
 - ⇒ **black box** analyses
 - ⇒ **deep/wide** neural networks are difficult to be interpreted
 - ⇒ requires prior “labeling” (i.e., categorization/knowledge about the processed data)
 - ⇒ requires big training datasets
 - ⇒ highly impacted by noise
 - ⇒ can recognize cats and dogs but cannot recognize horses if not pre-trained
 - ⇒ cannot discover something that we do not know already

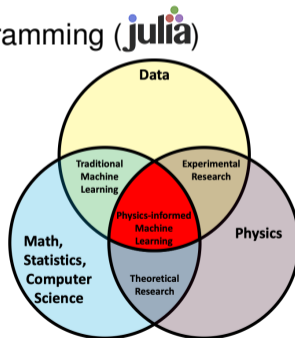


- ▶ **Supervised** ML: not good for science applications
- ▶ **Physics-informed** ML: learns from data but includes preconceived science knowledge
 - ⇒ needs SME inputs related to the analyzed problem
 - ⇒ requires smaller training datasets
 - ⇒ produces better predictability with lower uncertainty
 - ⇒ robust to data noise
 - ⇒ requires differentiable programming ()

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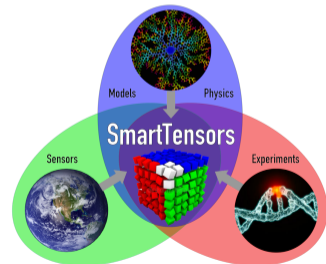
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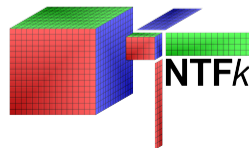
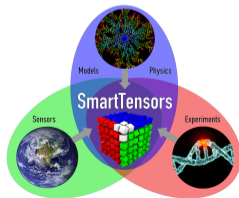
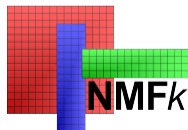
- ▶ **Supervised** ML: not good for science applications
- ▶ **Physics-informed** ML: designed for science applications
- ▶ **Unsupervised** ML: extracts features from data for **categorization** and **prediction**
 - ⇒ unbiased analyses not impacted by data labeling, subject-matter-expert opinions, and physics assumptions
 - ⇒ however, physics constraints/relationships/models can be added if needed
 - ⇒ identifies features that distinguish images of animals (e.g., cats, dogs, horses, etc.)
 - ⇒ categorizes the images so that SME's can identify ("label") the animals (geologic features)

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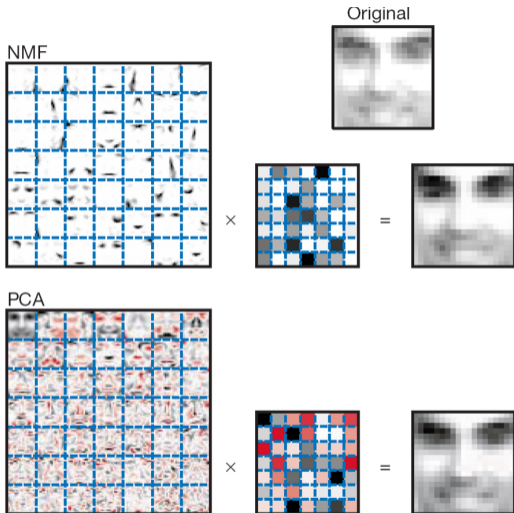
- ▶ **Supervised (Deep)** ML: major limitations for science applications
- ▶ **Physics-informed** ML: designed for science applications
- ▶ **Unsupervised** ML: designed for **Data Analytics** and **Model Diagnostics** problems
- ▶ **SmartTensors**: novel framework for **Unsupervised** and **Physics-informed** ML



- ▶ **SmartTensors**: Open-source framework for **Unsupervised** and **Physics-informed** Machine Learning (ML)
- ▶ <https://github.com/SmartTensors>
- ▶ Based on novel LANL-patented methods and computational techniques
- ▶ Involves matrix/tensor factorization coupled with custom k -means clustering
- ▶ Allows for nonnegativity/sparsity/physics constraints
- ▶ Capable to efficiently process large datasets (TB's) utilizing GPU's, & TPU's
- ▶ Coded in **julia**; orders of magnitude faster than Python, R and MATLAB

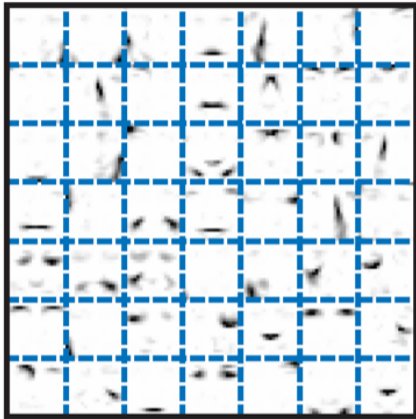


- ▶ NMF vs PCA (Lee & Seung, 1999)
- ▶ NMF: Nonnegative Matrix Factorization
- ▶ PCA: Principal Component Analysis

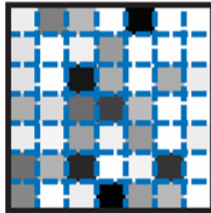


Nonnegativity constraints provide meaningful and interpretable results (+sparsity)

- ▶ **Tensors** (multi-dimensional/multi-modal/multi-way datasets) are everywhere:
 - ▶ observational data are typically a 5-D tensor (x, y, z, t, attributes)
 - ▶ model outputs are typically a 5-D tensor (x, y, z, t, attributes)
 - ▶ data dependency to N parameters will form a $(N + 5)$ -D tensor

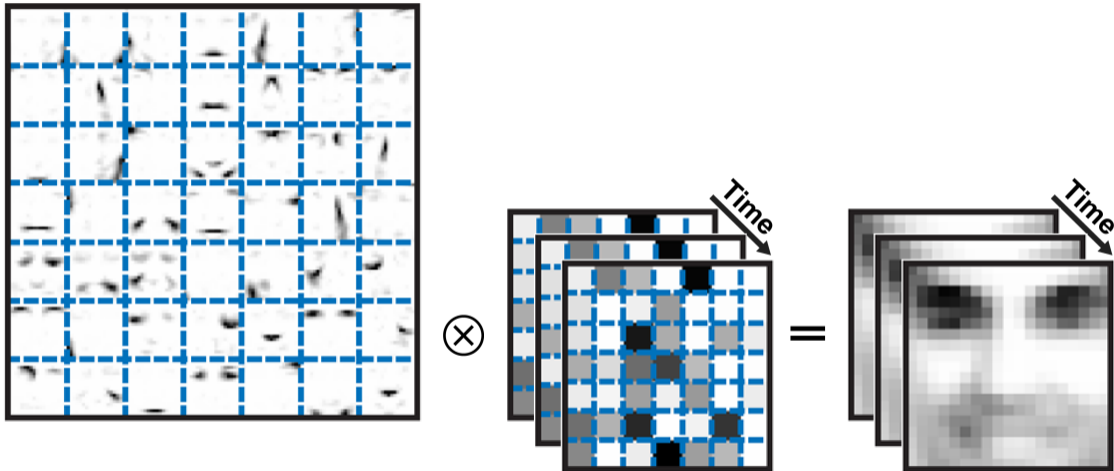


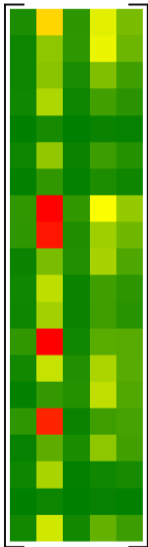
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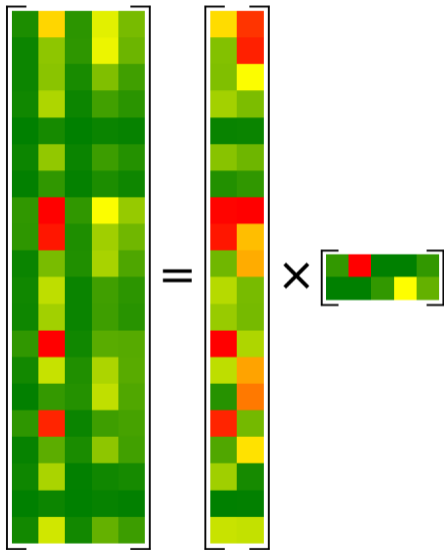






$$\mathbf{X}$$
$$[20 \times 5]$$

\mathbf{X} – data matrix
[attributes \times locations]



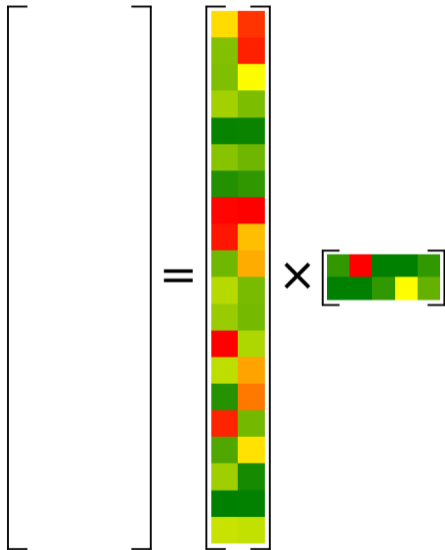
$$X = W \times H$$

$$[20 \times 5] = [20 \times 2] \times [2 \times 5]$$

X – **data** matrix
 [attributes × locations]

W – **feature (signal)** matrix
 [attributes × signatures]

H – **mixing** matrix
 [signatures × locations]



$$X = W \times H$$

$$[20 \times 5] = [20 \times 2] \times [2 \times 5]$$

X – **data** matrix

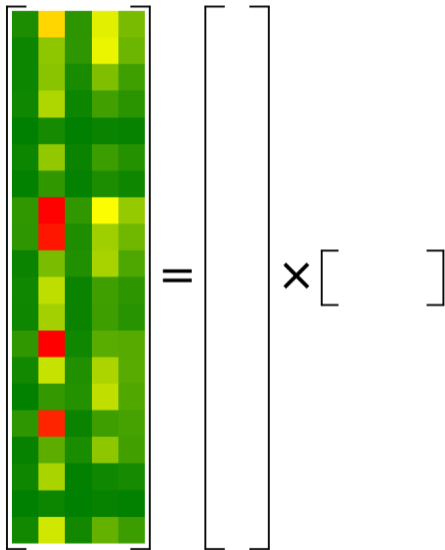
[attributes × locations]

W – **feature (signal)** matrix

[attributes × signatures]

H – **mixing** matrix

[signatures × locations]



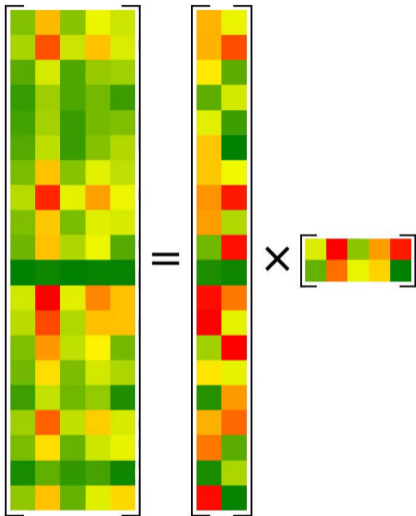
$$X = W \times H$$

$$[20 \times 5] = [20 \times ?] \times [? \times 5]$$

⇒ 100 **knowns**

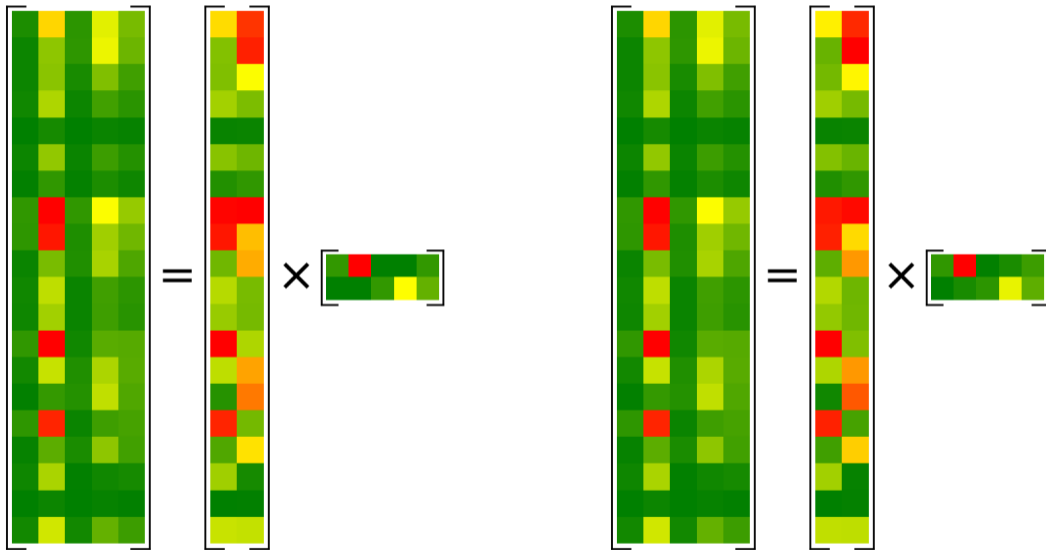
⇒ **unknown** number of signatures
(2 or more)

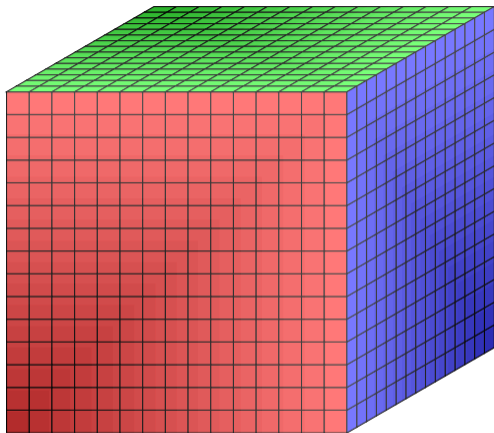
⇒ **unknown** matrix elements of W and H
(50 or more)



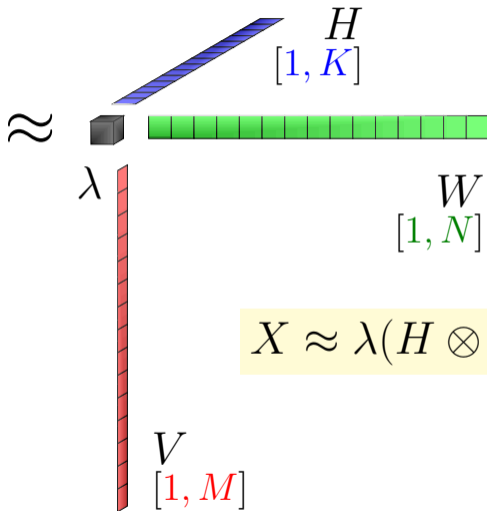
0001

NMF_k: true vs. estimated matrix factorization



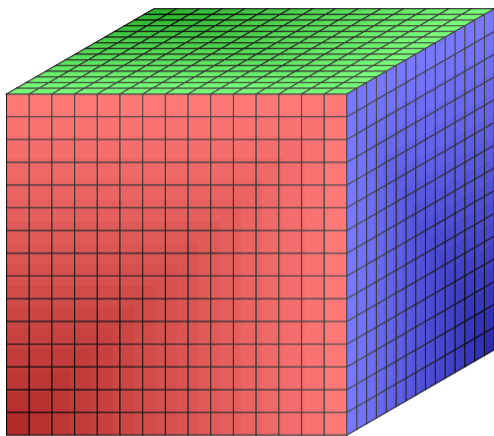


X
 $[K, M, N]$

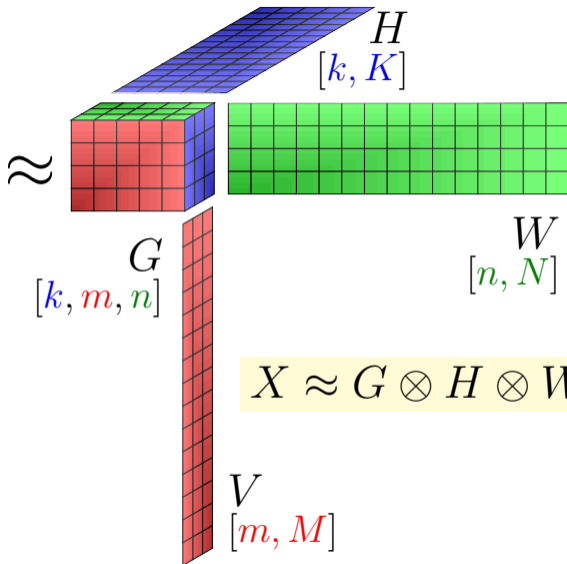


$$X \approx \lambda(H \otimes W \otimes V)$$

Tucker Tensor Decomposition (3D): Rank-60 / Multirank-(3,4,5) tensor

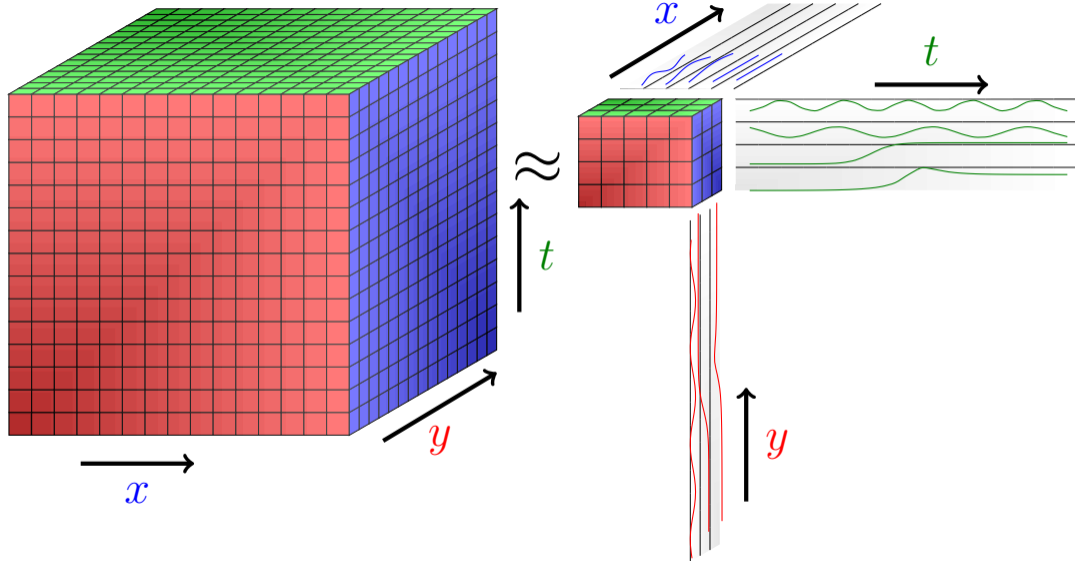


X
 $[K, M, N]$



$$X \approx G \otimes H \otimes W \otimes V$$

Tucker Tensor Decomposition (3D): Rank-60 / Multirank-(3,4,5) tensor



▶ **Field Data:**

- ▶ Contamination
- ▶ Climate
- ▶ Seismic
- ▶ **Geothermal**
- ▶ **Oil/gas production**
- ▶ CO₂ sequestration
- ▶ **Wildfires** (California 2020)
- ▶ **COVID-19**

▶ **Lab Data:**

- ▶ X-ray Spectroscopy
- ▶ UV Fluorescence Spectroscopy
- ▶ Microbial population analyses
- ▶ Isotope fractionation

▶ **Operational Data:**

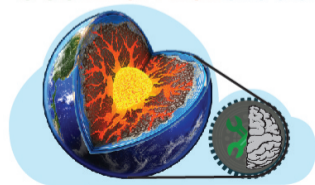
- ▶ LANSCE: Los Alamos Neutron Accelerator
- ▶ Oil/gas production
- ▶ CO₂ sequestration

▶ **Model Outputs:**

- ▶ Reactive mixing $A + B \rightarrow C$
- ▶ Co-polymer Phase separation
- ▶ Protein Molecular Dynamics
- ▶ Climate
- ▶ CO₂ sequestration
- ▶ Wildfires

- ▶ Funded by DOE GTO
- ▶ LANL partnership with Google, Descartes Lab, Stanford, and UT
- ▶ Apply ML to discover and extract new (unknown) geothermal signatures
- ▶ Categorize geothermal data and generate labeled datasets
- ▶ Identify high-value data acquisition strategies needed for geothermal exploration
- ▶ Develop a cloud-based ML framework for geothermal exploration by fusing big data and multi-physics models
- ▶ Test & validate that ML methods can blindly discover hidden geothermal signatures (signals)
- ▶ <https://github.com/SmartTensors/GeoThermalCloud.jl>

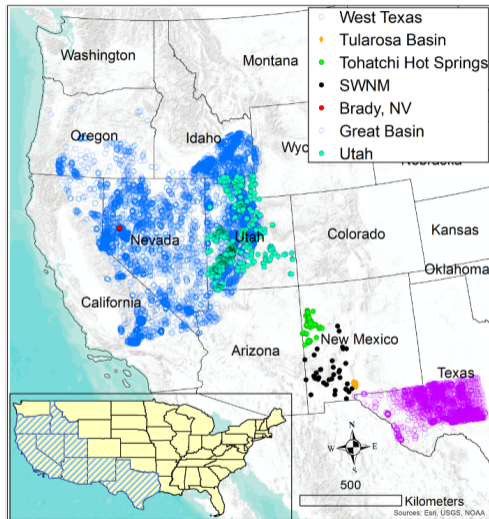
GeoThermalCloud

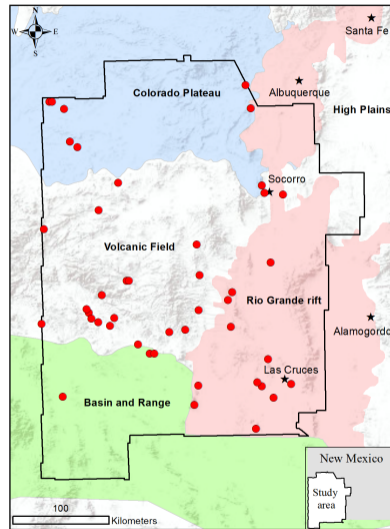


- ▶ Funded by ARPA E
- ▶ LANL partnership with Julia Computing, MIT, Stanford, and UNM
- ▶ Apply ML to Enhance Unconventional Energy Production
- ▶ Mine existing public and proprietary datasets to
 - (1) identify optimal well designs for energy extraction and
 - (2) predict blindly future oil & gas production



- ▶ Southwest New Mexico region
- ▶ Tularosa basin, New Mexico
- ▶ Tohachi basin, New Mexico
- ▶ Great Basin (Nevada, Oregon, Idaho, Utah, California)
- ▶ West Texas
- ▶ Hawaii
- ▶ Brady site, Nevada
- ▶ Geysers site, California
- ▶ Utah Forge site
- ▶ EGS Collab site





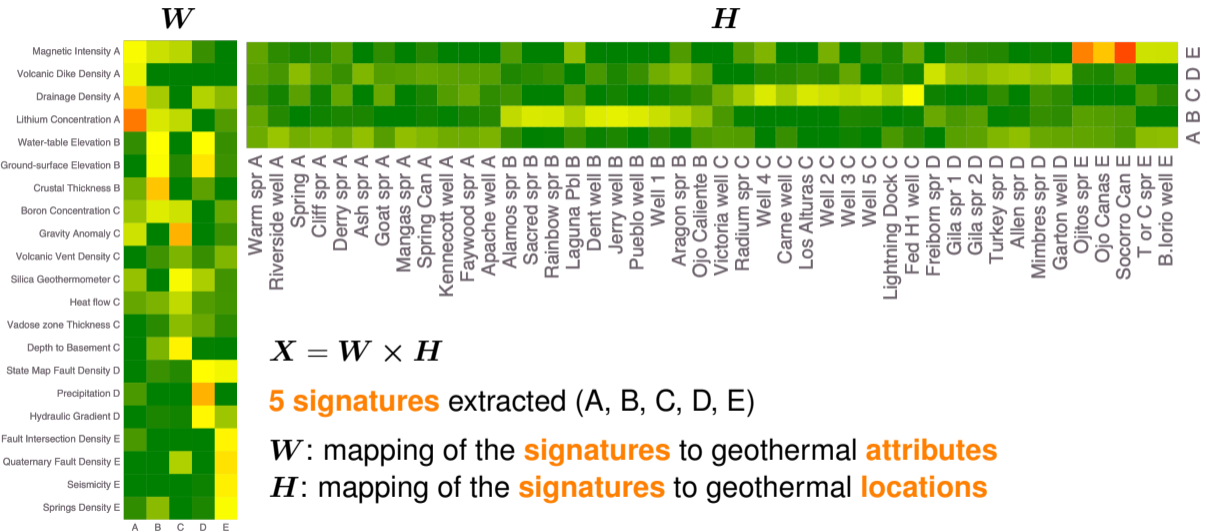
GeoThermalCloud: Southwest New Mexico: Data

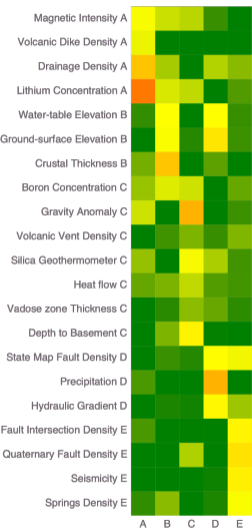
X^T [44 × 21]
[locations × attributes]

- ▶ Boron Concentration
- ▶ Gravity Anomaly
- ▶ Magnetic Intensity
- ▶ Volcanic Dike Density
- ▶ Drainage Density
- ▶ Fault Intersection Density
- ▶ Quaternary Fault Density
- ▶ Seismicity
- ▶ State Map Fault Density
- ▶ Springs Density
- ▶ Volcanic Vent Density
- ▶ Lithium Concentration
- ▶ Precipitation
- ▶ Silica Geothermometer Temp
- ▶ Hydraulic Gradient
- ▶ Watertable Elevation
- ▶ Heat flow
- ▶ Elevation
- ▶ Watertable Depth
- ▶ Crustal Thickness
- ▶ Depth to Basement

[Pepin, 2019]

Location	Boron	Gravity	Magnet	Dikes	Drain	Fault	Qfault	Seism	NMFIt	Springs	Vents	Lithium	Precip	Silica	Δh	WT	Qheat	Elev	DTW	Crust	Bsmt
Alamos Spring	-0.2	-203.3	136.2	0.431	7.4	0.000	0.000	0.004	16.2	0.010	0.003	-3.1	264.8	16.5	5.6	5812	4.6	1763	-21.5	38.7	1439
Allen Springs	-3.2	-189.3	184.6	3.625	17.3	0.000	0.001	0.002	15.6	0.003	0.001	-4.0	514.5	24.0	13.9	5994	4.4	1805	-20.1	32.5	51
Apache Tejo Warm Springs well	-1.8	-181.2	15.0	3.807	17.3	0.001	0.003	0.001	0.7	0.003	0.000	-8.6	326.3	52.0	4.7	5261	4.6	1641	34.6	30.7	24
Aragon Springs	1.5	-229.1	-317.7	0.010	19.0	0.000	0.000	0.000	41.1	0.005	0.003	-7.5	387.0	56.5	4.0	6981	4.5	2094	-30.1	38.8	1486
Ash Spring	-2.7	-193.2	66.6	4.914	17.0	0.000	0.000	0.002	9.3	0.003	0.000	-5.0	492.0	29.3	4.1	5712	4.4	1806	71.9	32.2	-92
B. Iorio 1 well	-2.1	-196.5	-48.2	1.936	18.8	0.057	21.02	0.000	9.1	0.003	0.003	-2.6	260.4	59.4	0.9	4240	4.0	1298	7.7	30.9	-188
Cliff Warm Spring	-2.5	-199.1	-47.1	1.290	22.8	0.001	2.58	0.002	11.0	0.002	0.001	-6.9	364.2	64.2	1.8	4546	4.2	1378	-6.7	33.1	-191
Dent windmill well	-2.1	-230.8	89.3	0.000	13.4	0.000	0.000	0.000	0.0	0.005	0.000	-7.3	341.7	19.7	2.4	6600	4.7	2108	94.3	43.5	865
Derry Warm Springs	-1.5	-161.6	197.0	0.659	18.3	0.007	9.16	0.000	15.9	0.002	0.000	-7.5	276.1	37.4	3.0	4183	4.6	1391	130.5	30.0	-120
Faywood Hot Springs	-2.6	-172.1	-49.8	0.939	16.6	0.002	2.81	0.000	1.9	0.003	0.000	-4.8	346.4	67.2	4.2	4910	5.5	1548	49.6	30.0	619
Federal H 1 well	-0.4	-132.0	35.0	0.000	5.8	0.004	20.31	0.001	7.2	0.000	0.015	-5.0	253.8	78.7	2.7	4104	4.9	1315	68.1	27.3	2906
Freiborn Canyon Spring	-2.5	-225.0	-242.0	0.401	13.1	0.000	0.000	0.001	19.8	0.001	0.004	-12.6	538.6	49.8	13.0	7123	4.6	2207	30.9	38.4	1138
Garton well	-3.2	-196.8	35.6	0.150	18.0	0.000	0.000	0.000	28.9	0.002	0.001	-5.0	489.9	70.0	4.3	6165	3.9	2037	146.4	30.9	-266
Gila Hot Springs 1	-1.9	-221.6	-149.3	0.127	24.2	0.000	0.000	0.001	25.5	0.003	0.003	-7.8	422.6	69.9	6.6	5867	4.4	1773	-25.7	34.0	413
Gila Hot Springs 2	-1.8	-222.9	-138.8	0.112	24.7	0.000	0.000	0.001	23.7	0.003	0.003	-6.7	425.9	70.8	3.2	5921	4.6	1811	-1.5	33.9	519
Goat Camp Spring	-2.1	-159.2	-29.7	0.751	10.0	0.001	2.22	0.007	10.6	0.002	0.001	-8.0	344.0	68.9	5.8	4480	4.4	1357	5.8	32.4	19
Jerry well	-0.8	-219.6	172.4	0.111	15.5	0.000	0.000	0.000	6.3	0.004	0.005	-7.9	243.9	13.4	1.0	6360	4.4	1947	6.3	42.3	1190
Kenecott Warm Springs well	-2.4	-178.3	-69.9	1.422	17.8	0.002	1.76	0.000	1.1	0.003	0.000	-6.9	355.0	66.1	4.3	4890	5.0	1520	28.9	30.0	409
Laguna Pueblo	0.4	-204.2	62.5	0.406	8.6	0.004	4.58	0.006	14.6	0.018	0.005	-3.3	259.7	42.9	2.6	5364	4.4	1628	-13.5	37.2	1506
Lightning Dock	-1.0	-168.0	-168.1	0.086	4.6	0.008	8.40	0.002	4.3	0.000	0.000	-3.9	291.5	107.3	0.8	4147	5.0	1278	14.3	29.8	1800
Los Alturas Estates	-1.5	-141.4	-127.5	0.004	7.6	0.003	0.005	0.002	6.6	0.001	0.000	-12.7	265.3	71.9	2.2	3892	6.3	1279	102.9	27.4	4321
Mangas Springs	-2.6	-201.0	-227.1	3.503	20.2	0.000	0.91	0.002	11.5	0.002	0.000	-4.5	393.5	53.6	0.3	4784	4.2	1459	-5.0	32.4	-178
Mimbres Hot Springs	-2.3	-200.6	43.4	0.670	15.4	0.002	1.13	0.000	19.0	0.004	0.000	-3.8	445.9	68.3	9.1	5914	4.9	1834	66.4	31.0	50
Ojitos Springs	-1.6	-202.1	-7.5	1.342	19.6	0.044	19.74	0.037	31.0	0.020	0.005	-4.5	257.5	57.6	7.2	5227	4.5	1594	2.3	33.0	-255
Ojo Caliente	-2.6	-226.5	-168.4	0.000	20.5	0.000	0.000	0.000	8.3	0.004	0.000	-2.9	333.6	48.4	3.5	6263	5.5	1987	74.0	33.8	2415
Ojo De las Canas	-1.7	-188.5	-85.8	0.839	22.3	0.036	12.55	0.036	28.0	0.013	0.003	-6.0	270.5	14.2	4.0	5003	4.5	1585	54.7	31.8	101
Pueblo windmill well	-1.2	-228.8	315.9	0.029	15.2	0.000	0.000	0.000	6.1	0.004	0.003	-12.0	265.8	18.3	2.9	6419	4.3	1963	6.0	42.5	1027
Radium Hot Springs	-0.8	-151.4	-7.8	0.010	8.8	0.013	11.40	0.003	10.6	0.001	0.000	-5.3	264.2	63.6	0.3	3982	5.4	1229	24.4	28.2	1191
Rainbow Spring	-1.7	-227.1	-48.5	0.000	11.0	0.000	0.000	0.001	0.0	0.006	0.000	-7.0	307.8	21.7	3.3	6269	4.7	1955	52.0	43.9	755
Riverside Store well	-1.3	-196.1	-102.9	1.562	22.6	0.000	2.50	0.002	11.7	0.002	0.001	-2.4	356.1	60.8	0.9	4489	4.3	1368	2.8	32.9	-165
Sacred Spring	-1.8	-228.4	-80.4	0.000	10.9	0.000	0.000	0.001	0.0	0.006	0.000	-7.0	298.4	21.2	1.3	6271	4.6	1940	29.7	43.9	742
Socorro Canyon	-1.8	-204.7	-136.5	1.203	21.1	0.051	28.88	0.034	33.8	0.020	0.005	-6.7	284.1	44.6	11.1	5237	5.0	1692	67.7	32.6	-229
Spring	-4.1	-183.5	334.5	0.218	20.1	0.011	1.81	0.000	20.1	0.001	0.006	-6.8	361.9	117.2	5.1	5472	3.8	1759	88.1	31.5	-104
Spring Canyon Warm Spring	-2.1	-194.2	117.3	2.293	21.9	0.000	1.50	0.002	12.7	0.002	0.000	-8.3	361.7	51.6	5.8	4576	4.2	1457	60.2	32.6	-57
Truth or Consequences spring	-1.1	-168.2	-54.3	2.175	18.4	0.064	20.51	0.000	10.3	0.003	0.002	-3.3	265.9	55.3	0.6	4255	4.3	1293	-8.4	31.0	304
Turkey Creek Spring	-3.2	-196.4	54.8	0.984	19.2	0.001	3.69	0.002	28.1	0.002	0.002	-3.7	493.4	81.3	5.8	5478	4.4	1718	7.7	33.6	56
Victoria Land and Cattle Co. well	-1.8	-165.9	-65.4	0.478	6.4	0.003	0.006	0.001	0.9	0.001	0.000	-2.9	253.0	43.0	1.9	4762	4.1	1616	9.6	30.7	2014
Warm Springs	-2.1	-193.3	113.5	0.220	19.0	0.029	2.63	0.000	16.5	0.004	0.003	-2.5	314.6	56.0	5.4	5777	4.3	1797	-1.7	32.7	1252
Well 1	-1.4	-230.7	-31.3	1.190	15.7	0.000	0.75	0.001	22.1	0.004	0.002	-6.6	345.4	49.0	1.7	7382	4.4	2249	1.8	40.0	1961
Well 2	-1.2	-162.5	0.8	0.000	4.5	0.008	24.24	0.003	11.8	0.000	0.006	-10.1	279.5	70.5	1.7	4291	4.8	1355	49.7	27.8	2993
Well 3	-2.5	-140.0	31.7	0.839	2.1	0.001	2.11	0.001	5.0	0.001	0.000	-7.3	369.0	51.0	4.1	4765	4.3	1907	431.7	28.0	3073
Well 4	-1.3	-161.7	-56.1	0.000	3.4	0.008	28.49	0.003	10.6	0.000	0.006	-10.0	274.3	94.0	1.9	4082	4.7	1338	91.3	27.7	3373
Well 5	-1.9	-167.2	-29.9	0.000	2.5	0.008	15.48	0.002	3.1	0.000	0.005	-6.8	243.8	47.0	0.3	3839	4.0	1276	106.1	27.4	5460
Well south of Carne	-2.4	-156.7	-129.6	0.457	4.3	0.000	2.11	0.002	6.0	0.001	0.000	-6.8	269.7	87.1	1.4	4109	4.5	1275	13.5	28.4	2761





Dominant signature attributes:

- Signature C**

- ▶ Volcanic Vent Density
- ▶ Gravity Anomaly
- ▶ Heat flow
- ▶ Silica Geothermometer
- ▶ Watertable Depth
- ▶ Depth to Basement
- ▶ Boron

- Signature A**

- ▶ Volcanic Dike Density
- ▶ Magnetic Intensity
- ▶ Drainage Density
- ▶ Lithium

- Signature B**

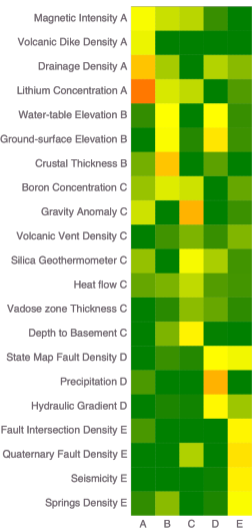
- ▶ Water-table Elevation
- ▶ Ground-surface Elevation
- ▶ Crustal Thickness

- Signature D**

- ▶ Precipitation
- ▶ Hydraulic Gradient
- ▶ State Map Fault Density

- Signature E**

- ▶ Seismicity
- ▶ Fault Intersection Density
- ▶ Quaternary Fault Density
- ▶ Springs Density



Physics interpretation:

- Signature C: Deep heat flow**

- ▶ Volcanic Vent Density
- ▶ Gravity Anomaly
- ▶ Heat flow
- ▶ Silica Geothermometer
- ▶ Watertable Depth
- ▶ Depth to Basement
- ▶ Boron

- Signature A: Shallow heat flow**

- ▶ Volcanic Dike Density
- ▶ Magnetic Intensity
- ▶ Drainage Density
- ▶ Lithium

- Signature B: Lateral hydraulics**

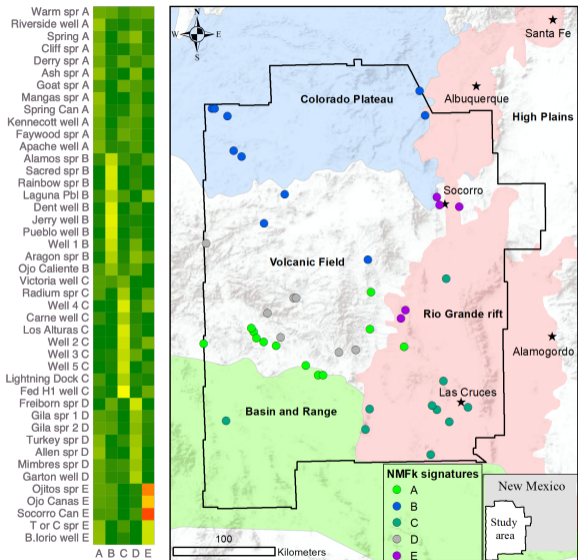
- ▶ Water-table Elevation
- ▶ Ground-surface Elevation
- ▶ Crustal Thickness

- Signature D: Vertical hydraulics**

- ▶ Precipitation
- ▶ Hydraulic Gradient
- ▶ State Map Fault Density

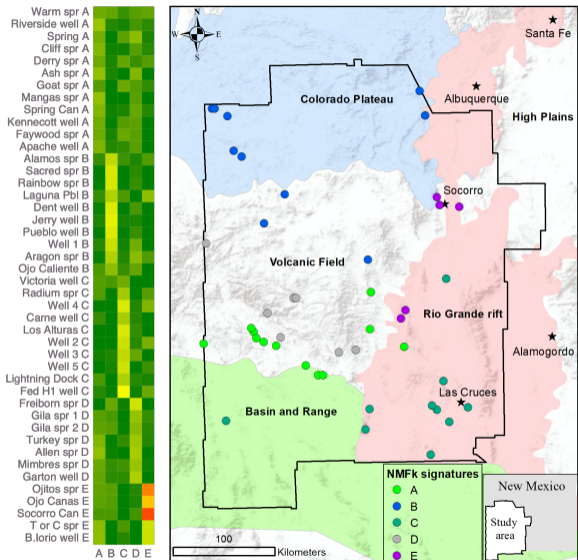
- Signature E: Tectonics**

- ▶ Seismicity
- ▶ Fault Intersection Density
- ▶ Quaternary Fault Density
- ▶ Springs Density



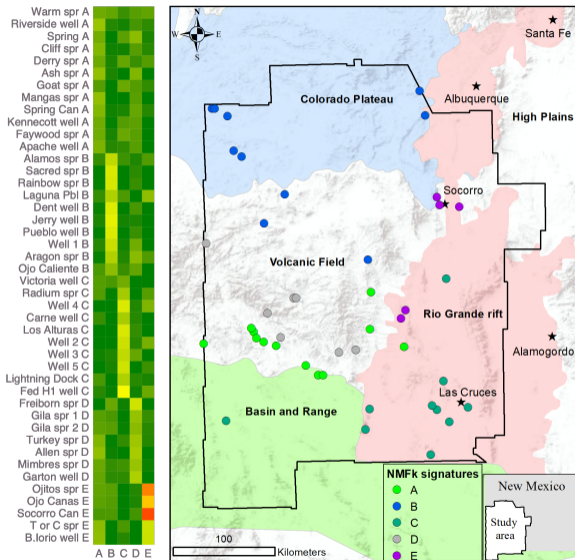
Province association:

- Signature B:
Colorado Plateau
- Signature C:
Basin and Range
- Signature D:
Volcanic Field #1
- Signature A:
Volcanic Field #2
- Signature E:
Rift Zone



Province association:

- Signature B:
Colorado Plateau
- Signature C:
Basin and Range
- Signature D:
Volcanic Field #1
- Signature A:
Volcanic Field #2
- Signature E:
Rift Zone



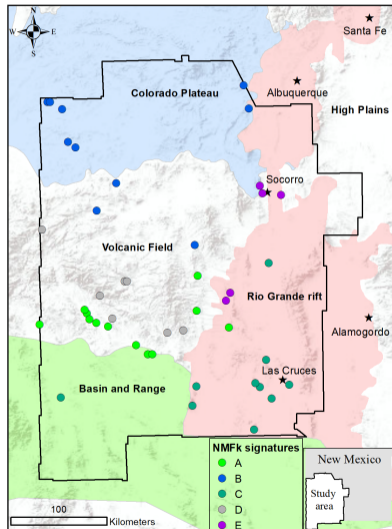
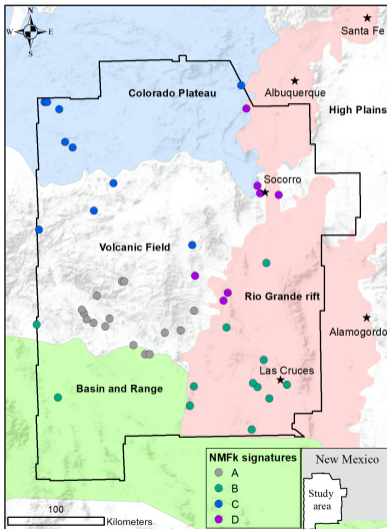
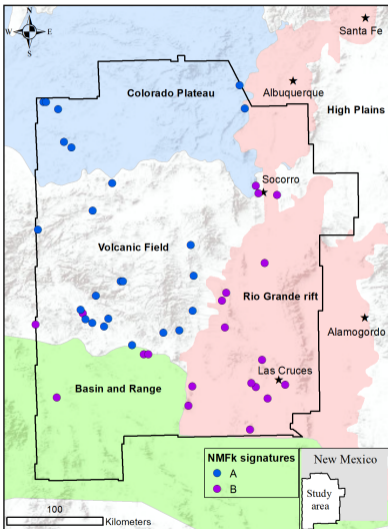
Physics/province association:

- Signature B:
Colorado Plateau ⇔ **Lateral hydraulics**
- Signature C:
Basin and Range ⇔ **Deep heat flow**
- Signature D:
Volcanic Field #1 ⇔ **Vertical hydraulics**
- Signature A:
Volcanic Field #2 ⇔ **Shallow heat flow**
- Signature E:
Rift Zone ⇔ **Tectonics**

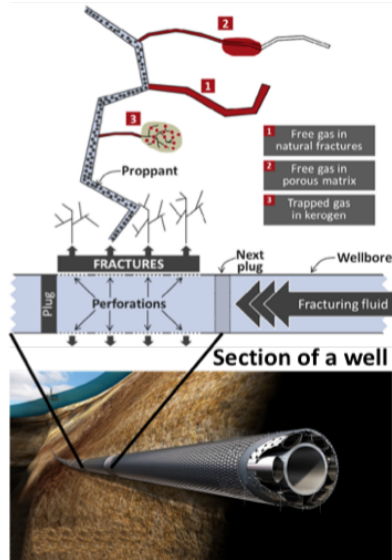
2 signatures

4 signatures

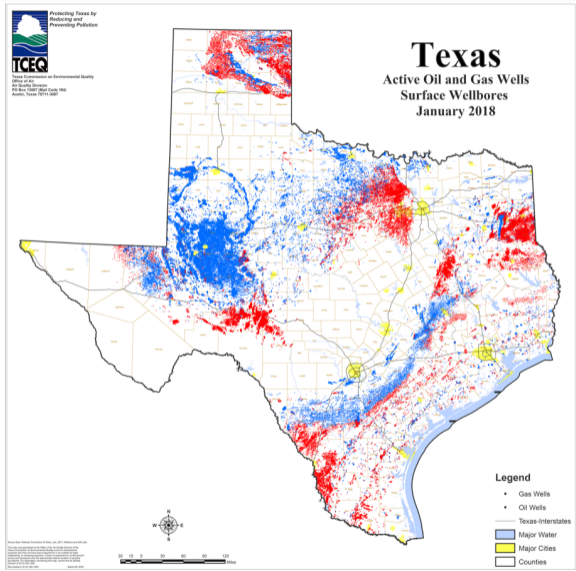
5 signatures



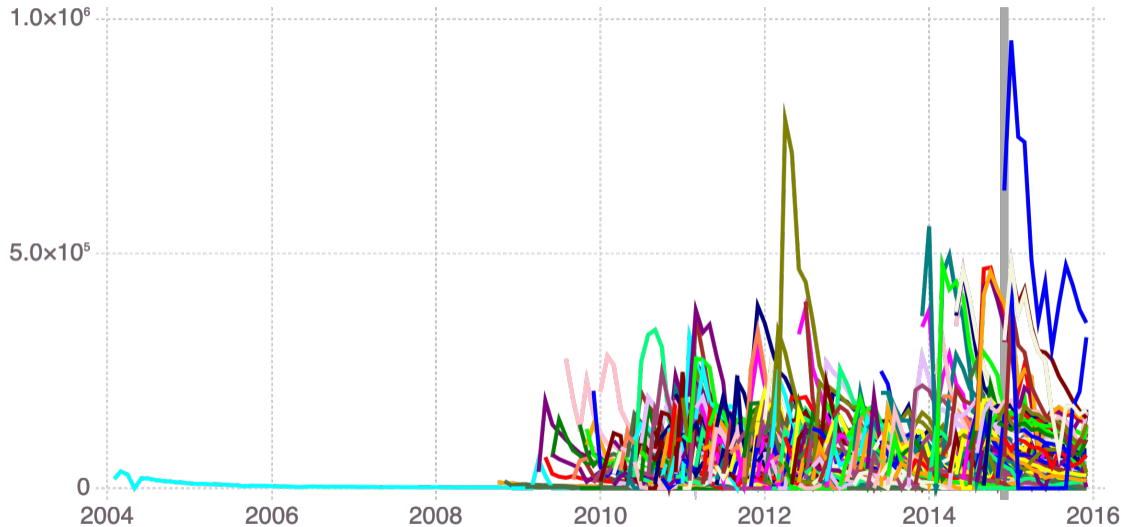
- ▶ Oil/Gas production from unconventional reservoirs extracts a small portion of the available resources (<10%)
- ▶ Oil/Gas production is challenging to predict and optimize
- ▶ Physics processes during well development (including hydrofracking) and extraction are poorly understood and challenging to simulate
- ▶ Alternative is to learn to predict system behavior based on the observed oil/gas production at existing wells



- ▶ Large public datasets are available representing unconventional oil and gas production (U.S. and world wide)
- ▶ Data represent monthly production rates (oil, gas, water) + many other well attributes
- ▶ ~ 2,000,000 wells in U.S.
- ▶ > 300,000 wells in Texas
- ▶ > 20,000 wells in Eagle Ford Shale Play
- ▶ 327 gas wells in Eagle Ford Shale Play selected for preliminary analyses

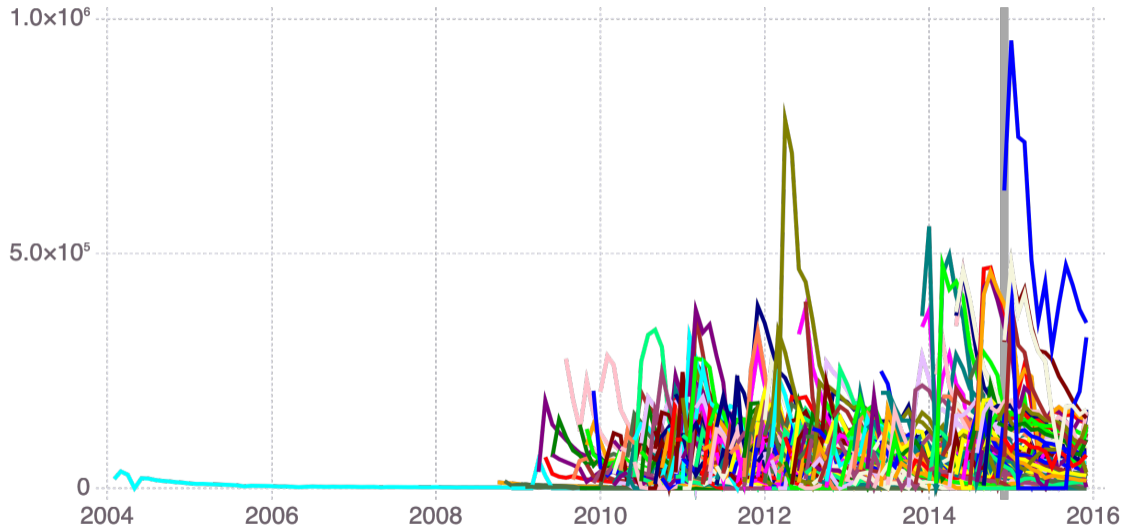


Eagle Ford Shale Play: Monthly production volumes [MCF] of 327 gas wells

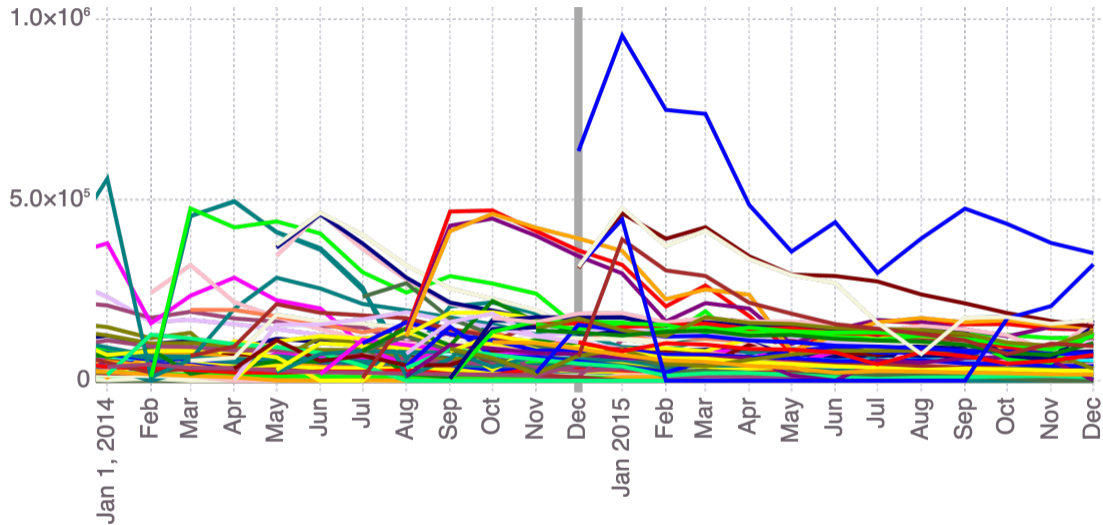


- ▶ Use all the data up to a given cutoff date (e.g. 2015)
- ▶ Apply ML to learn behavior of the “known“ well transients
 - Identify and group wells which behave similarly (having similar production transients)
 - Discover the optimal number of **master decline curves** required to reproduce the observed transients
 - **master decline curves** represent production **features/signatures**
- ▶ Apply ML to predict **blindly** the unknown production transients beyond the cutoff
- ▶ Prediction is obtained by discovering to which type (group) the wells producing beyond the cutoff belong
- ▶ i.e., discovering what combinations of the **master decline curves** can represent the wells producing beyond the cutoff
- ▶ Unsupervised ML analyses performed using **SmartTensors**

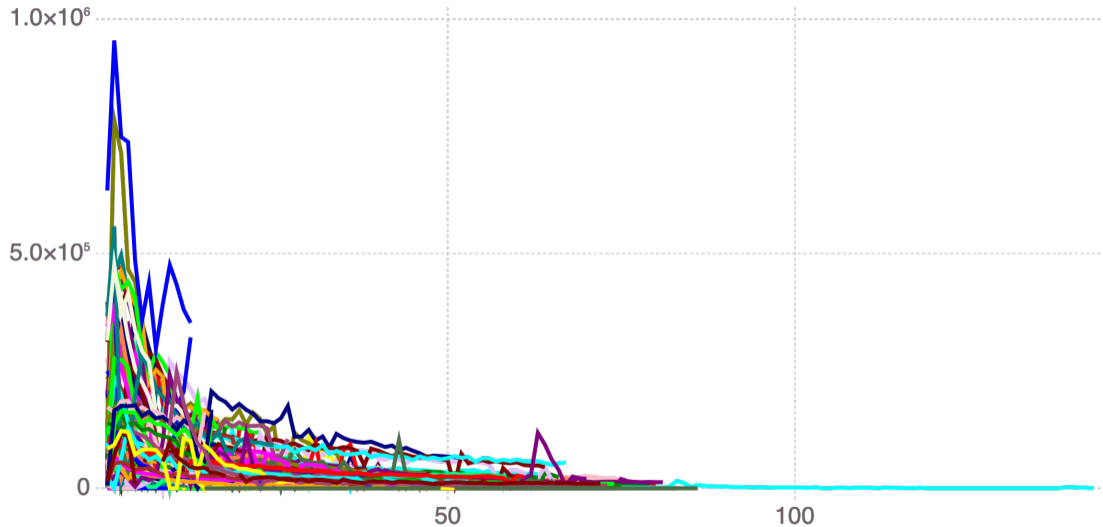
Eagle Ford Shale Play: Monthly production volumes [MCF] of 327 gas wells



Eagle Ford Shale Play: Monthly production volumes [MCF] of 327 gas wells

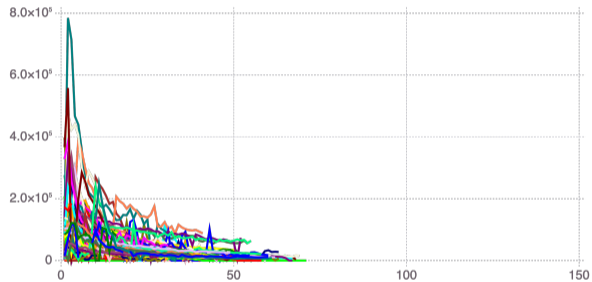
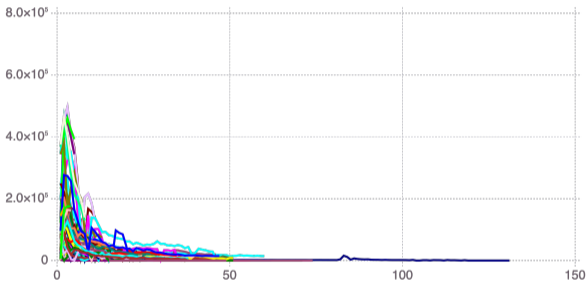


Eagle Ford Shale Play: Monthly production volumes [MCF] of 327 gas wells

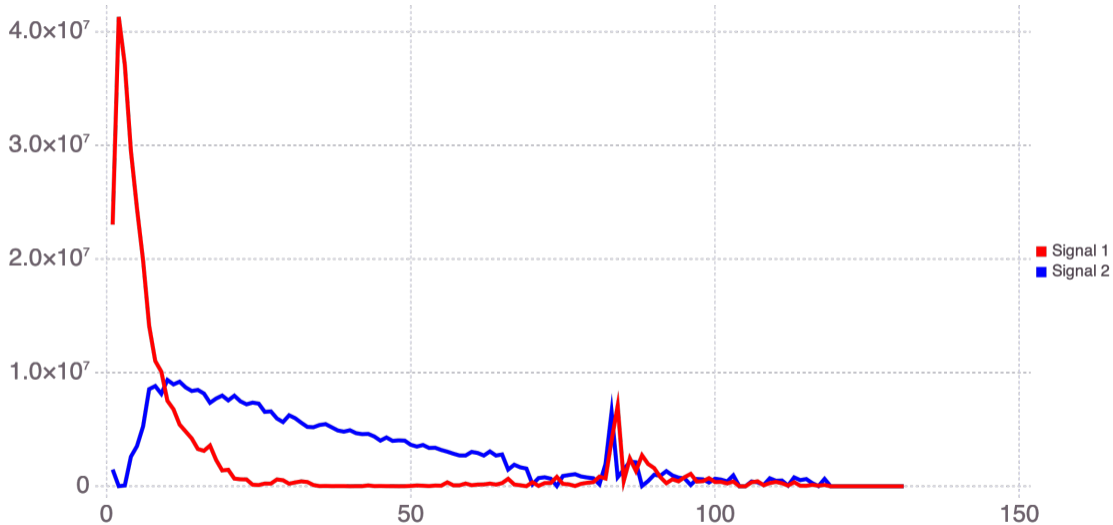


'Fast' declining (135)

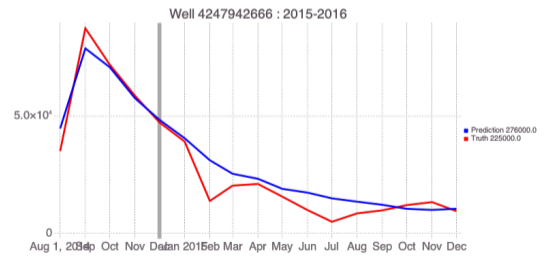
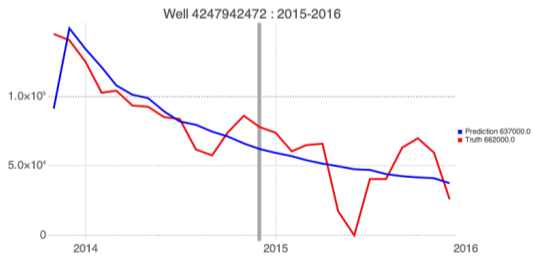
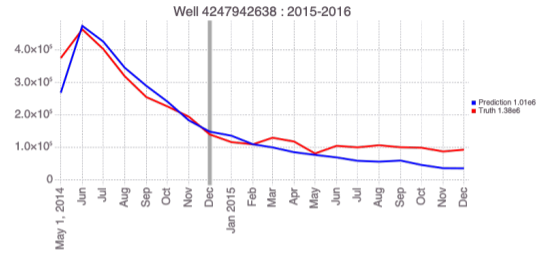
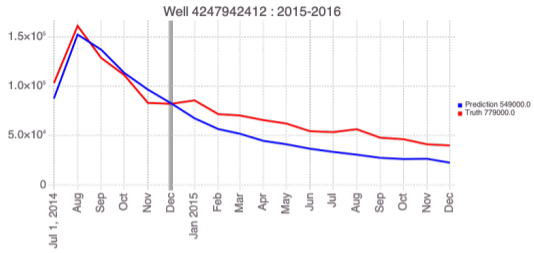
'Slow' declining (192)



Eagle Ford Shale Play: Master Decline Curves [MCF over months]

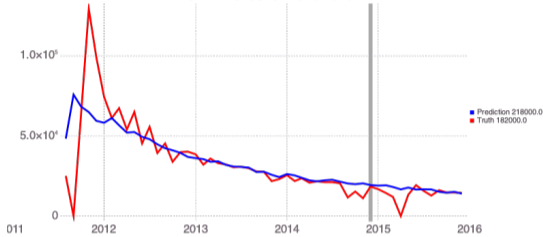


Eagle Ford Shale Play: Blind predictions beyond 2015

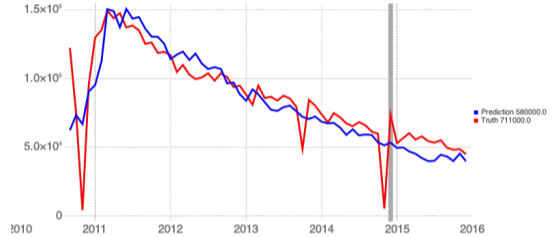


Eagle Ford Shale Play: Blind predictions beyond 2015

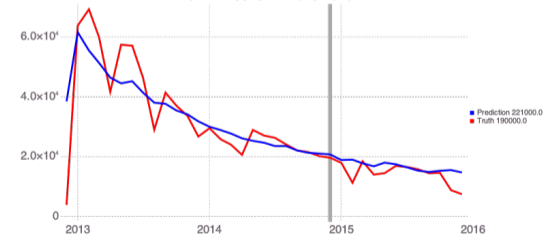
Well 4247940978 : 2015-2016



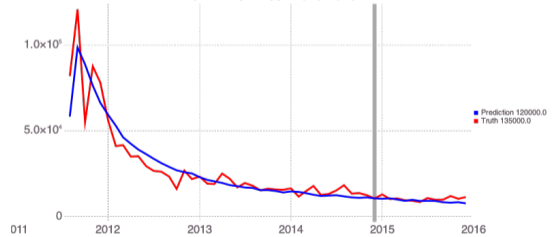
Well 4247940815 : 2015-2016



Well 4212332547 : 2015-2016



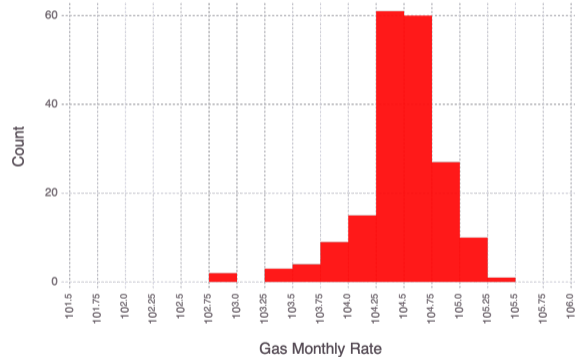
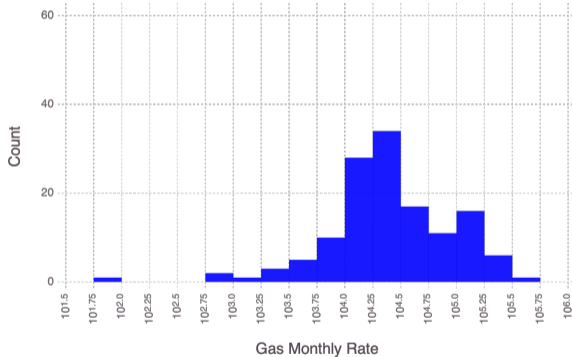
Well 4247941283 : 2015-2016



Monthly rate histograms

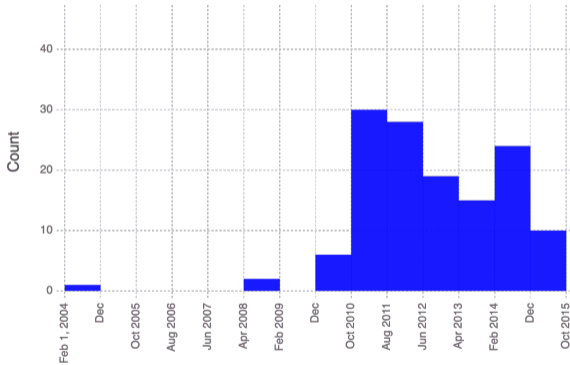
'Fast' declining (135)

'Slow' declining (192)

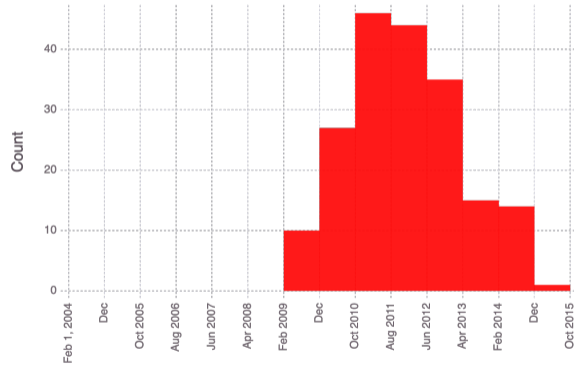


Drilling date histograms

'Fast' declining (135)

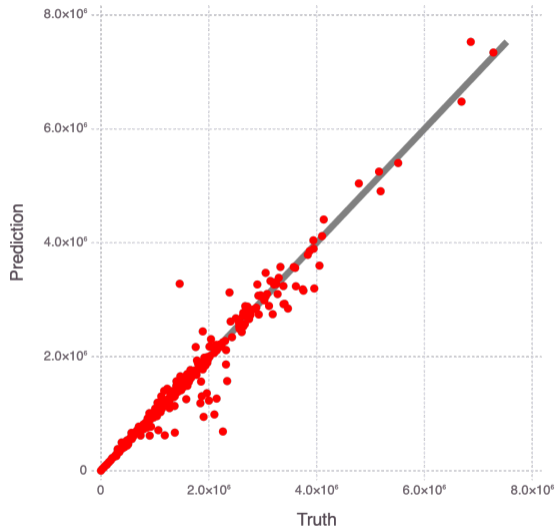


'Slow' declining (192)

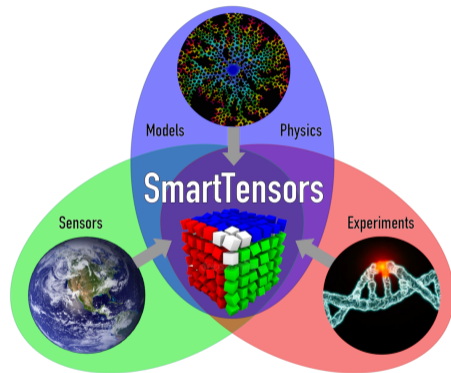


- ▶ Other well attributes also differ between the 2 groups
- ▶ For example:
 - Operators
 - Proppant mass
 - Injected fluid volumes
 - ...

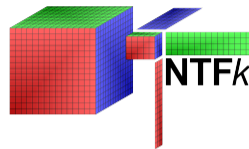
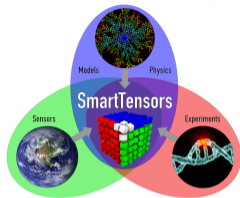
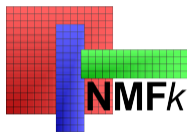
- ▶ 300 wells continue producing beyond 2015
- ▶ $r^2 = 0.96$
- ▶ Mehana et al., Machine-Learning Predictions of the Shale Wells Performance, Journal of Natural Gas Science and Engineering, 2021, 10.1016/j.jngse.2021.103819



- ▶ **SmartTensors**: novel unsupervised and physics-informed ML methods and computational tools
- ▶ Some of the **SmartTensors** tools have been recently patented
- ▶ **SmartTensors** have been applied successfully to geothermal and oil/gas energy extraction problems
- ▶ **SmartTensors** have been also used to solve a diverse set of real-world problems including human cancer, climate, COVID-19, and California wildfires



- ▶ **SmartTensors** codes are open source and widely used



- ▶ **SmartTensors** codes, documentation and examples:

<http://tensors.lanl.gov>

<https://smarttensors.github.io>

<https://github.com/SmartTensors>

<https://github.com/SmartTensors/GeoThermalCloud.jl>

- ▶ **SmartTensors** workshop at GSA

Machine Learning in Geosciences Friday, Oct 1, 2021

<https://community.geosociety.org/gsa2021/science-careers/courses>
registration opens soon!