# Machine learning analyses for characterization of oil, gas and water production from unconventional tight-rock reservoirs

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http://tensors.lanl.gov

- **Supervised** ML: learns everything from data
  $\Rightarrow$ requires big training datasets
  $\Rightarrow$ highly impacted by noise
  $\Rightarrow$ cannot discover something that we do not know already
- **Physics-informed** ML: learns from data but includes preconceived knowledge about the governing processes
  $\Rightarrow$ requires smaller training datasets
  $\Rightarrow$ produces better predictability with lower uncertainty
  $\Rightarrow$ robust to data noise
- **Unsupervised** ML: extracts features from data that can be applied for categorization and prediction
  $\Rightarrow$ unbiased analyses not impacted by data labeling and physics assumptions

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# Unsupervised Machine Learning Applications: Data Analytics / Model Diagnostics

- Feature extraction (**FE**)
- Blind source separation (**BSS**)
- Detection of disruptions / anomalies
- Image recognition
- Separate physics processes
- Discover unknown dependencies and phenomena
- Develop reduced-order/surrogate models
- Identify dependencies between model inputs and outputs
- Guide development of physics models representing the data
- Make predictions
- Optimize data acquisition
- "Label" datasets for supervised ML analyses

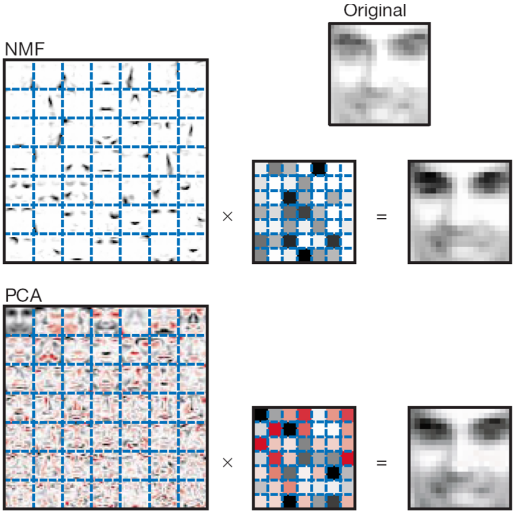
# Nonnegative Matrix/Tensor Factorization

- Novel LANL-patented, open-source, unsupervised Machine Learning (ML) methods and computational techniques
- Based in matrix/tensor factorization coupled with custom $k$-means clustering and nonnegativity/sparsity constraints:
  - NMF$k$: Nonnegative **Matrix** Factorization
  - NTF$k$: Nonnegative **Tensor** Factorization
  - `https://github.com/TensorDecompositions`
- Capable to efficiently process large datasets (TB's) utilizing GPU's, TPU's & FPGA's

  $\Rightarrow$ julia, Flux.jl, Knet.jl, AutoOffLoad.jl, Zygote.jl, TensorFlow, PyTorch, MXNet

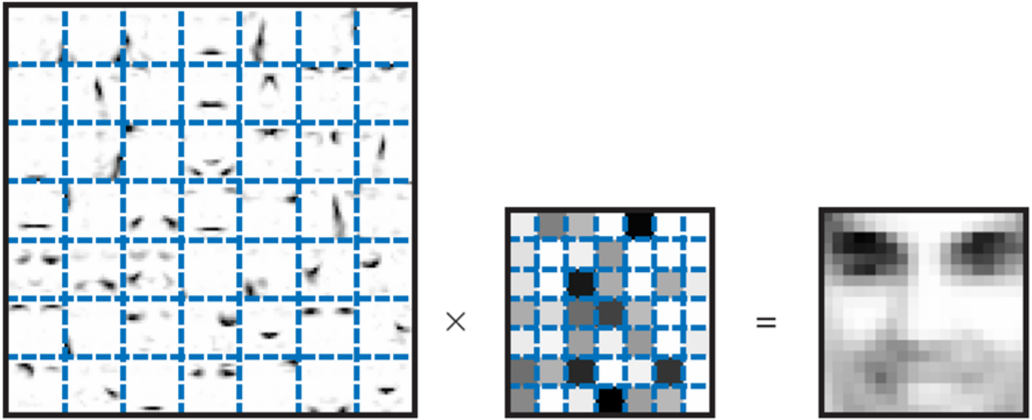
# Why nonnegativity?

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

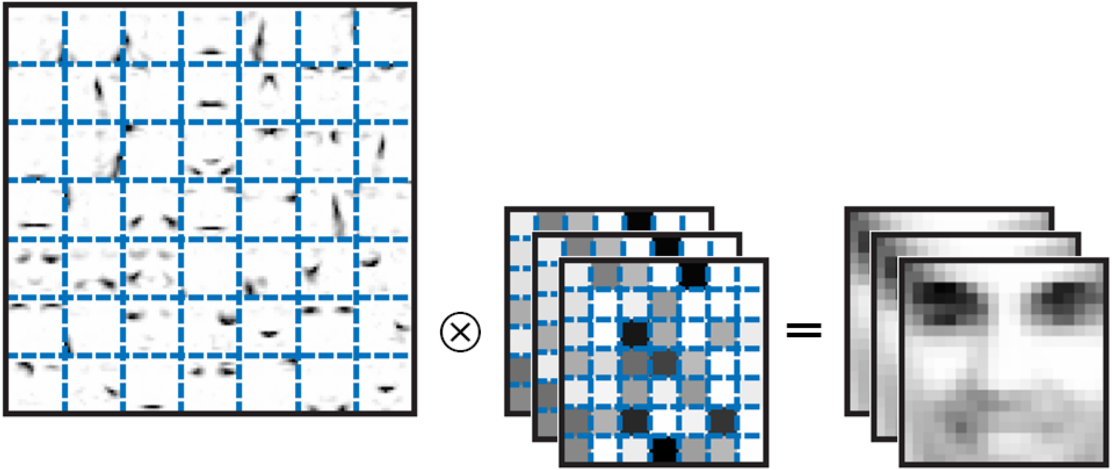



**Nonnegativity constraints provide meaningful and interpretable results (+sparsity)**

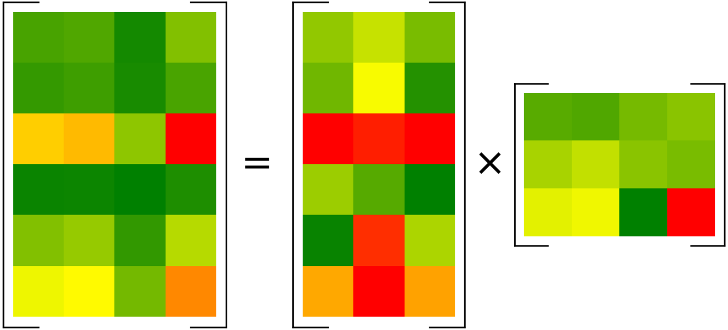
# NMF: Nonnegative Matrix Factorization



# NTF: Nonnegative Tensor Factorization

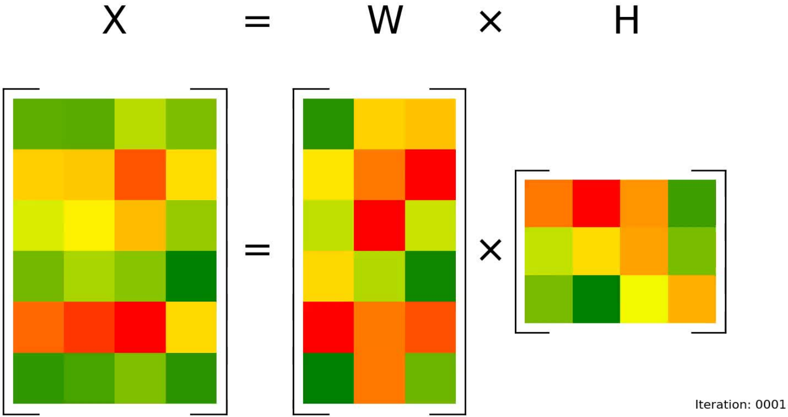


X = W × H

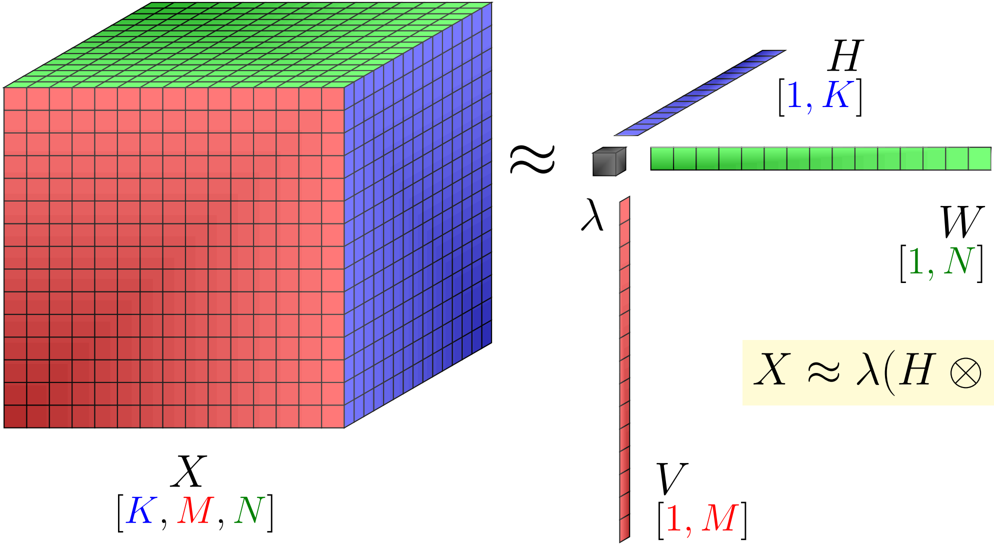


$24$ knowns $(6 \times 4) \rightarrow 30$ unknowns $(6 \times 3) + (3 \times 4)$
number of features $k$ is also unknown (here, $k = 3$))

# NMFk: Factorization process

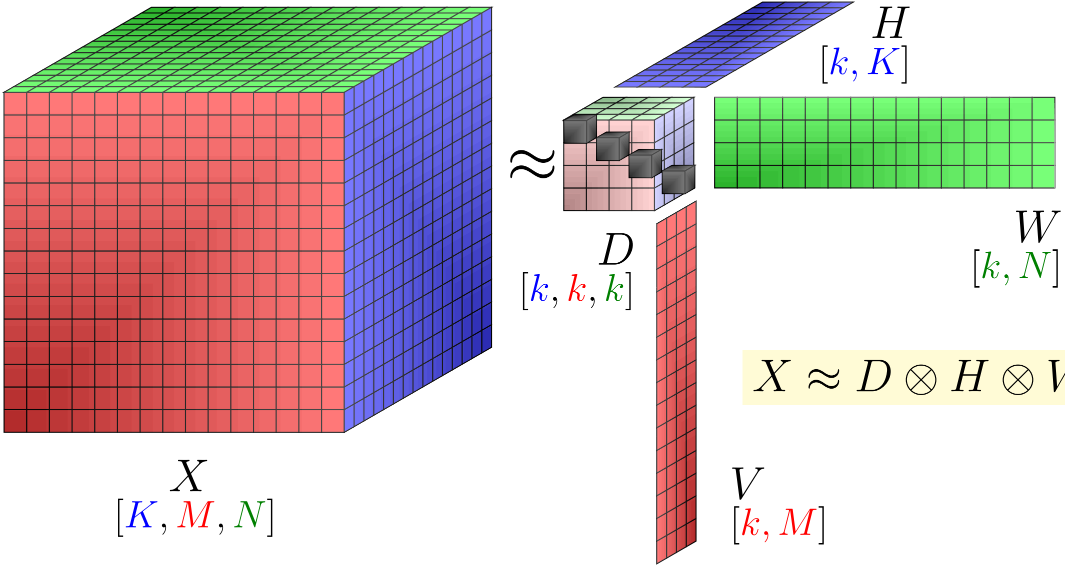


# Tensor Decomposition (3D case): Rank-1 tensor



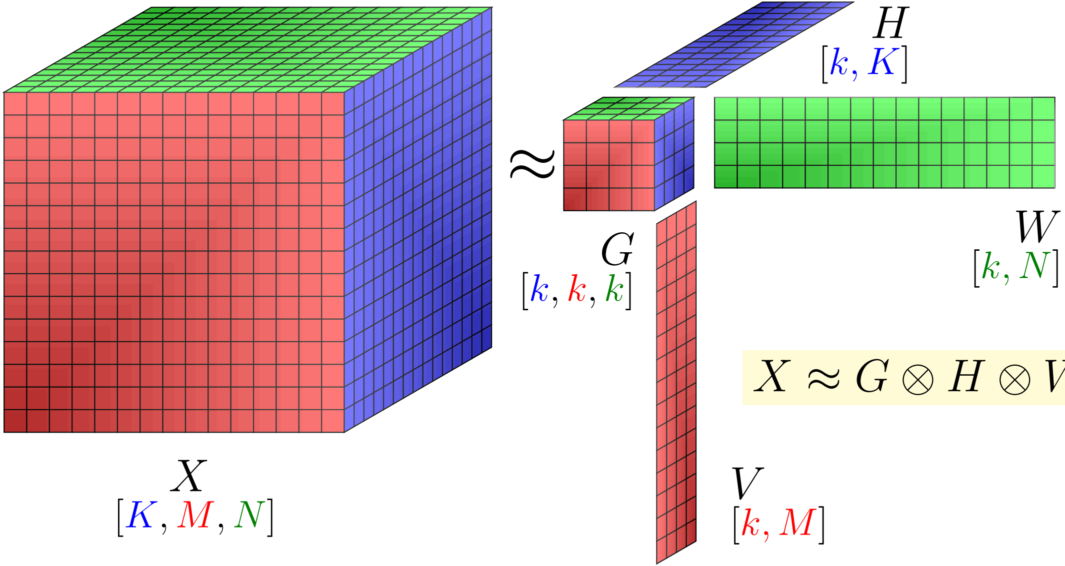

$$X \approx \lambda(H \otimes W \otimes V)$$

# Tensor Decomposition (3D case): Rank-4 tensor



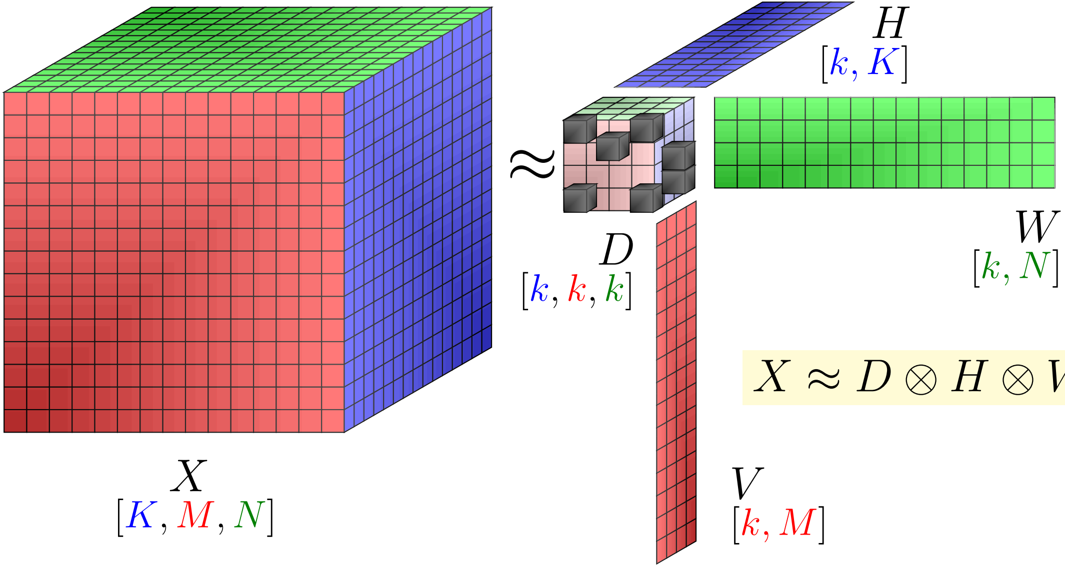

$$X \approx D \otimes H \otimes W \otimes V$$

# Tensor Decomposition (3D case): Rank-64 / Multirank-(4,4,4) tensor




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

# Tucker Tensor Decomposition (3D case): Rank-7 Multirank-(3,3,4)




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

# NMF$k$ / NTF$k$ Analyses

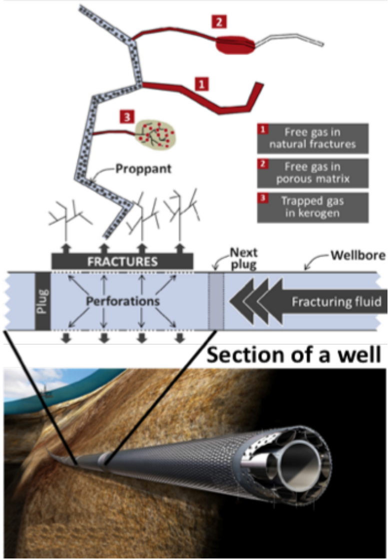
- **Field Data**:
  - Contamination
  - Climate
  - Geothermal
  - Seismic
  - Oil/gas production
- **Lab Data**:
  - X-ray Spectroscopy
  - UV Fluorescence Spectroscopy
  - Microbial population analyses
  - Isotope fractionation
- **Operational Data**:
  - LANSCE: Los Alamos Neutron Accelerator
  - Oil/gas production
- **Model Outputs**:
  - Reactive mixing $A + B \to C$
  - Phase separation of co-polymers
  - Molecular Dynamics of proteins
  - Climate modeling

# NMF$k$ / NTF$k$ Publications

- Vesselinov, Munuduru, Karra, O'Maley, Alexandrov, Unsupervised Machine Learning Based on Non-Negative Tensor Factorization for Analyzing Reactive-Mixing, **Journal of Computational Physics**, Special issue: Machine Learning, 2019.
- Stanev, Vesselinov, Kusne, Antoszewski, Takeuchi, Alexandrov, Unsupervised Phase Mapping of X-ray Diffraction Data by Nonnegative Matrix Factorization Integrated with Custom Clustering, **Nature Computational Materials**, 2018.
- Vesselinov, O'Malley, Alexandrov, Nonnegative Tensor Factorization for Contaminant Source Identification, **Journal of Contaminant Hydrology**, 2018.
- O'Malley, Vesselinov, Alexandrov, Alexandrov, Nonnegative/binary matrix factorization with a D-Wave quantum annealer, **PLOS ONE**, 2018.
- Vesselinov, O'Malley, Alexandrov, Contaminant source identification using semi-supervised machine learning, **Journal of Contaminant Hydrology**, 2017.
- Alexandrov, Vesselinov, Blind source separation for groundwater level analysis based on nonnegative matrix factorization, **WRR**, 2014.

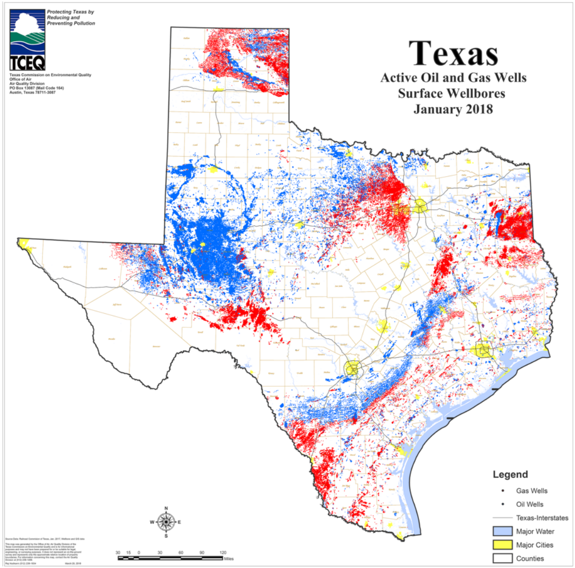
# Oil/Gas Production

- 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

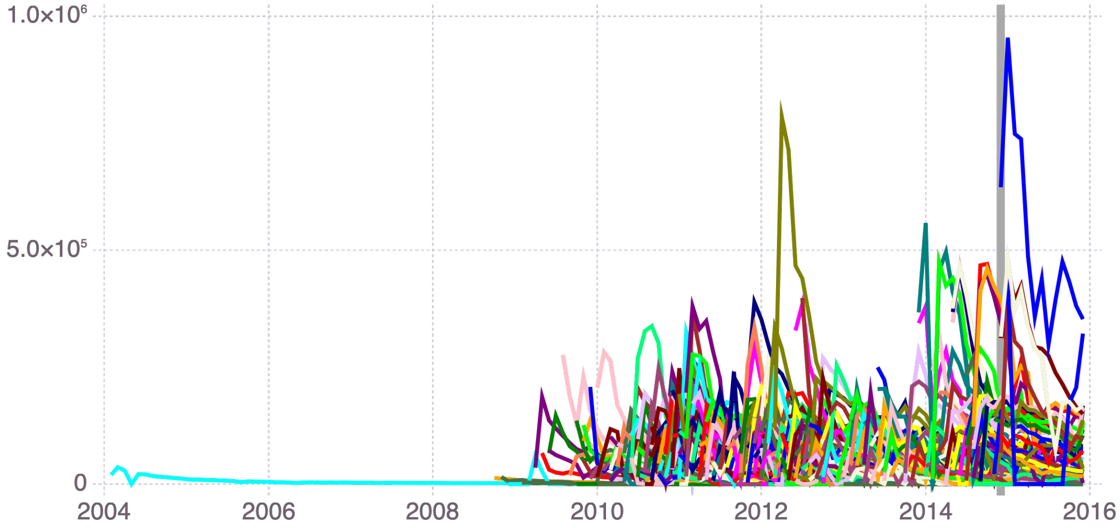


# Oil/Gas Production Data

- 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
- $\sim$ 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



# ML analysis of Oil/Gas Production Data

- 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 represent the observed transients
  - **master decline curves** = production **features** or **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
- ML analyses performed using **NMFk**/**NTFk**

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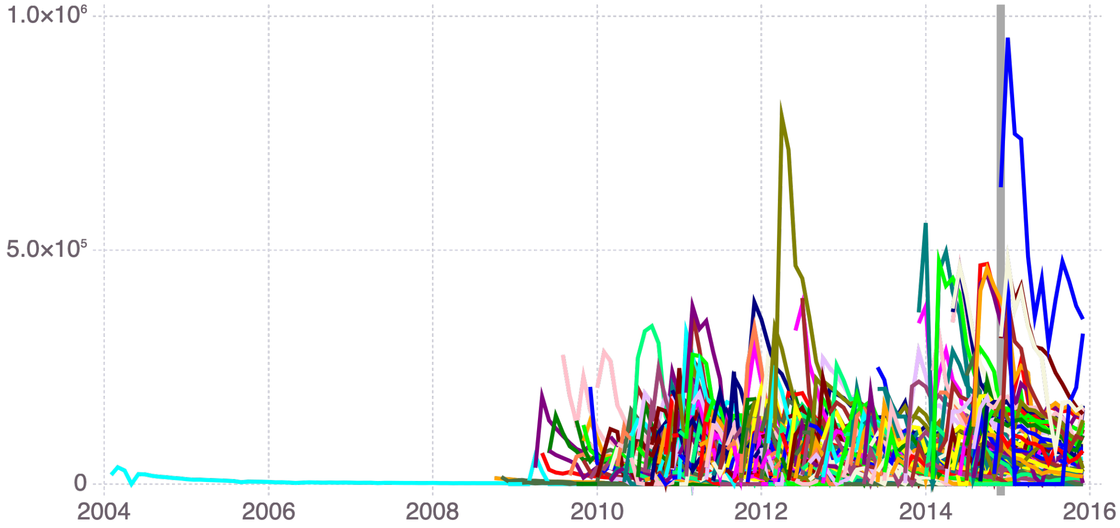

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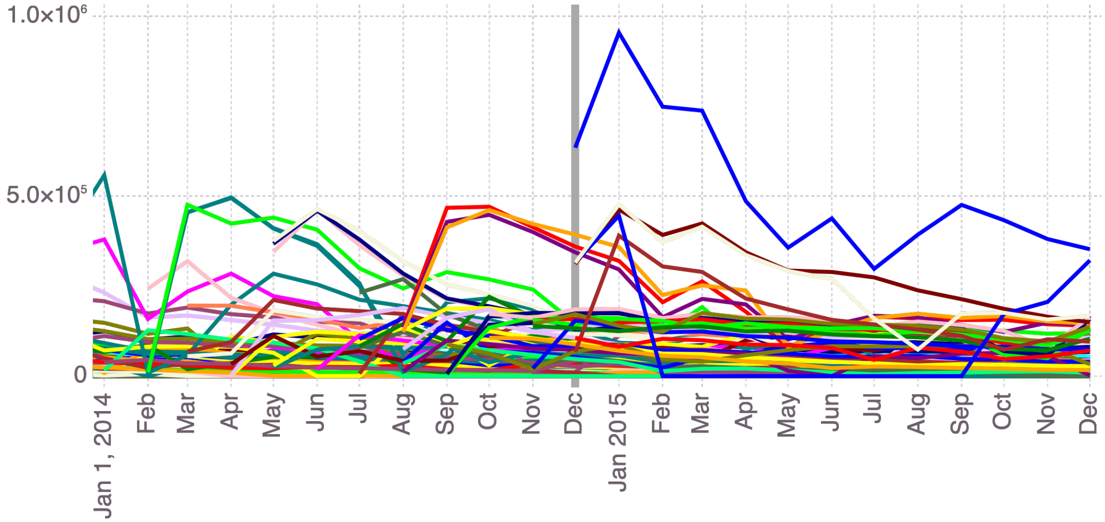

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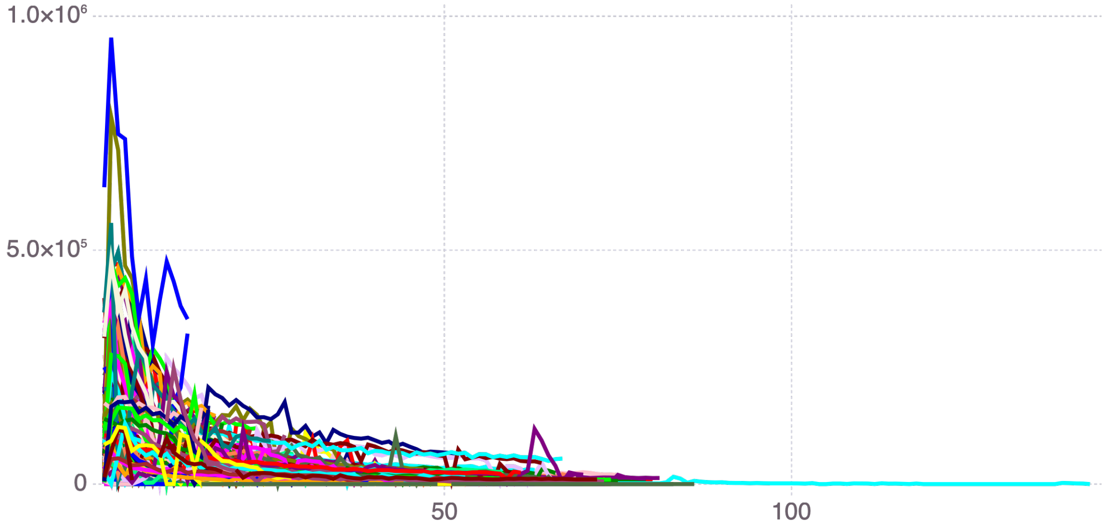
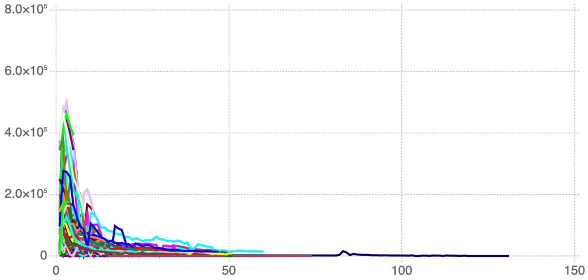
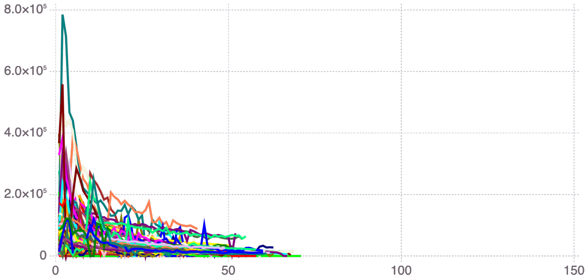


# Eagle Ford Shale Play: Wells split into 2 groups

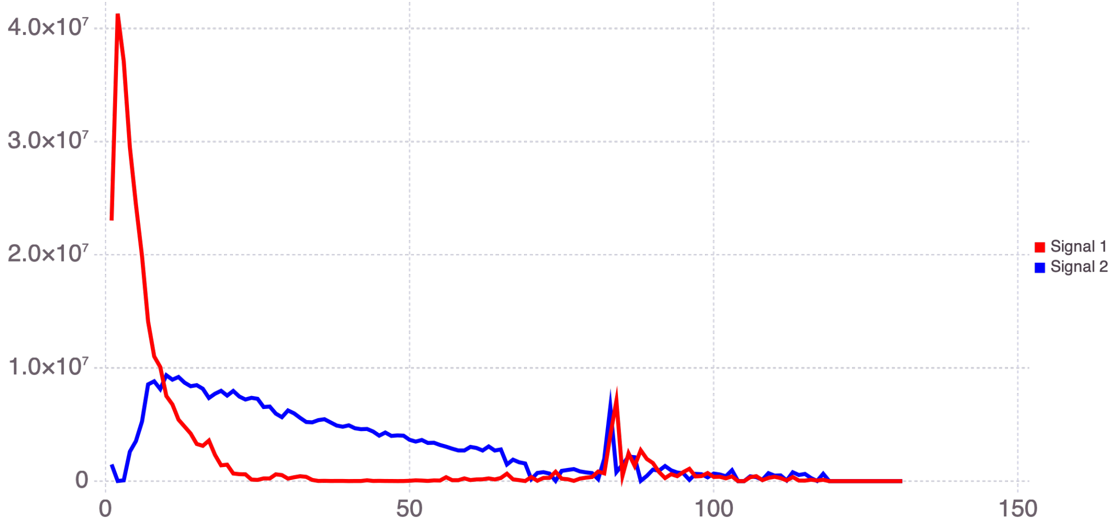
## 'Fast" declining (135)



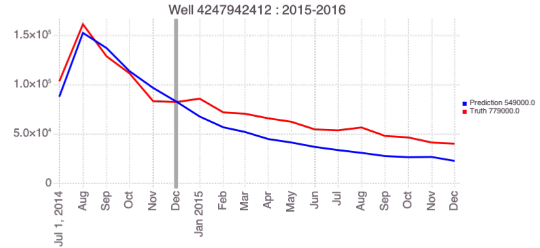

## 'Slow" declining (192)

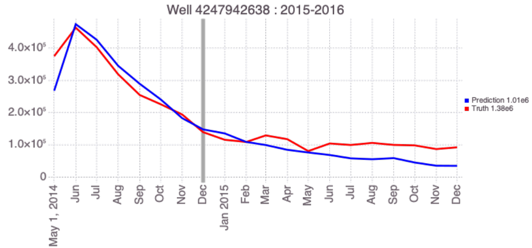


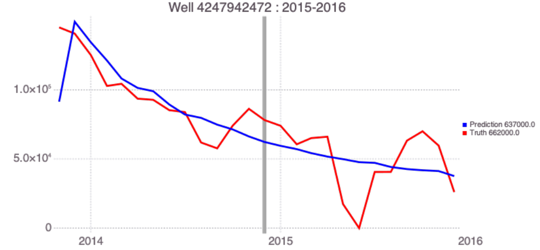
# Eagle Ford Shale Play: Master Decline Curves [MCF over months]

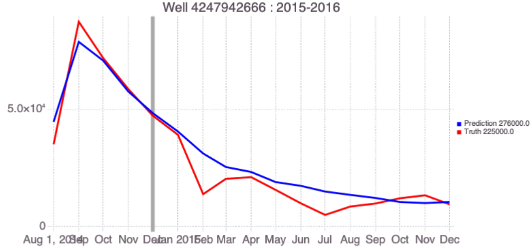


# Eagle Ford Shale Play: Blind predictions beyond 2015



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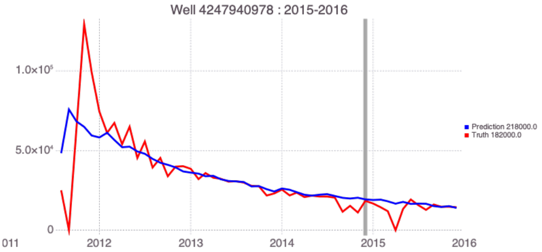
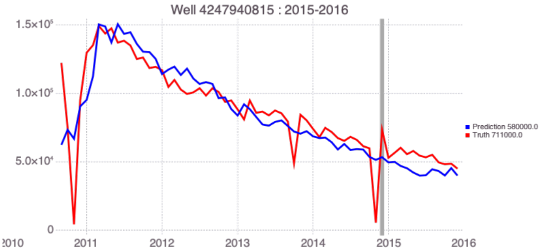
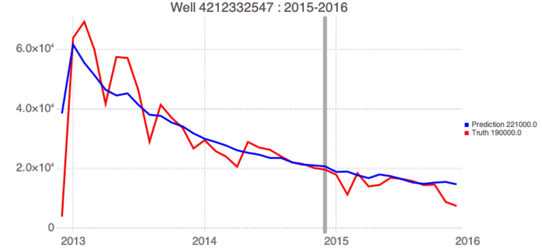
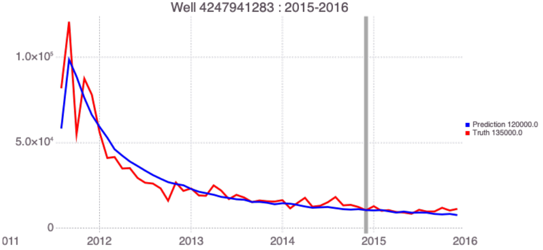


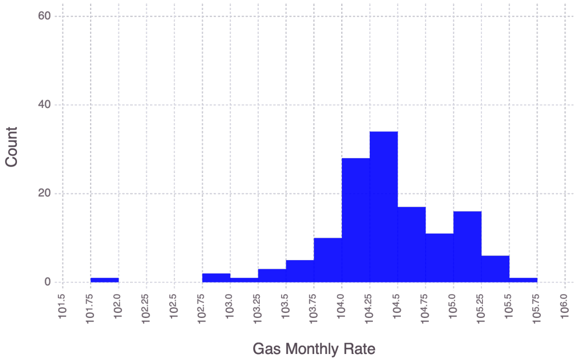



## Monthly rate histograms

### ‘Fast” declining (135)

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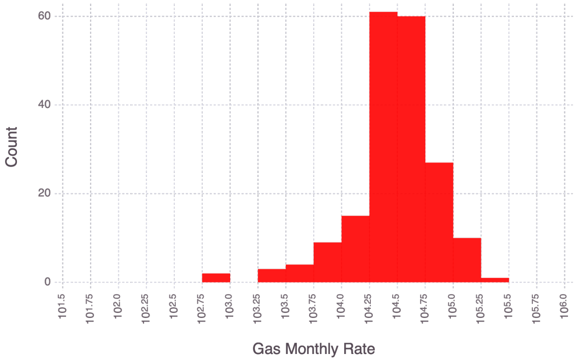
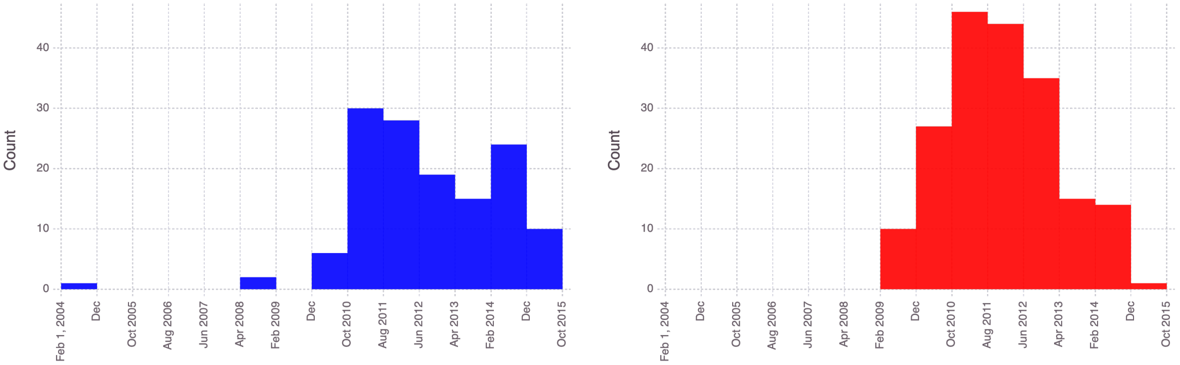


## Drilling date histograms

**'Fast" declining** (135) **'Slow" declining** (192)

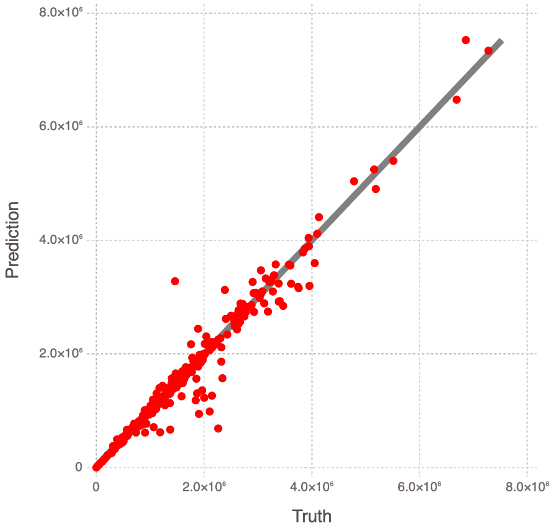


# Eagle Ford Shale Play: Wells split into 2 groups

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

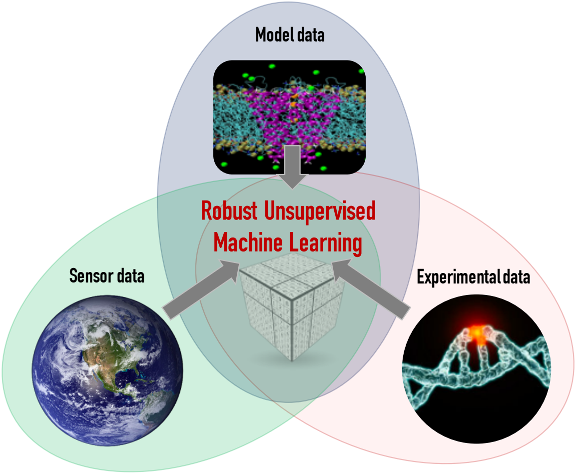
# Eagle Ford Shale Play: Blind predictions beyond 2015

- 300 wells continue producing beyond 2015
- $r^2 = 0.96$



# Summary

- Developed **novel** unsupervised and physics-informed ML methods and computational tools
- Our ML methods have been used to solve various real-world problems (brought breakthrough discoveries related to human cancer research)
- julia



# Machine Learning (ML) Algorithms / Codes developed by our team

- Codes:

NMF$k$ | MADS | NTF$k$

- Examples:

http://madsjulia.github.io/Mads.jl/Examples/blind_source_separation
http://tensors.lanl.gov
http://tensordecompositions.github.io
https://github.com/TensorDecompositions
https://hub.docker.com/u/montyvesselinov