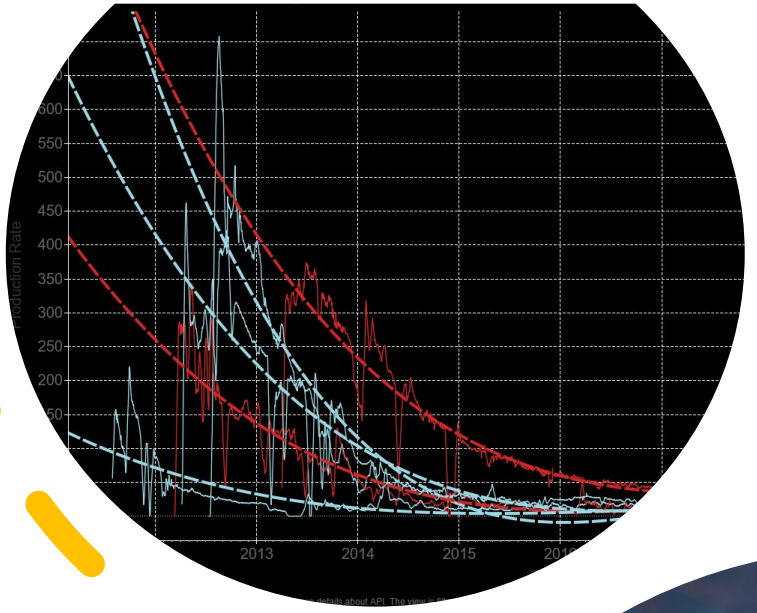
Combining Machine Learning and Empirical Engineering Methods Towards Improving Oil Production Forecasting



Andrew Allen

Thesis Defense

June 19th, 2020

Thesis Committee Chair: Dr. Roy Jafari-Marandi

LEARN BY DOING
CAL POLY
College of Engineering

Outline

- Introduction and Significance
- Background
- Literature Review
- Case Study
- Conclusions
- Questions

About Student

- *Academic Background*
  - B.S. and M.S Industrial Engineering
  - Graduate courses focused on data science and analytics
- *Career Interests*
  - Business Intelligence and Data Analytics
  - Energy, sustainability, and continuous improvement
- *Research Motivation*
  - *Learn by doing* approach to solve real-engineering problem
- *Research Goals*
  - Build off existing skills and prepare for entering workforce

Introduction and Significance

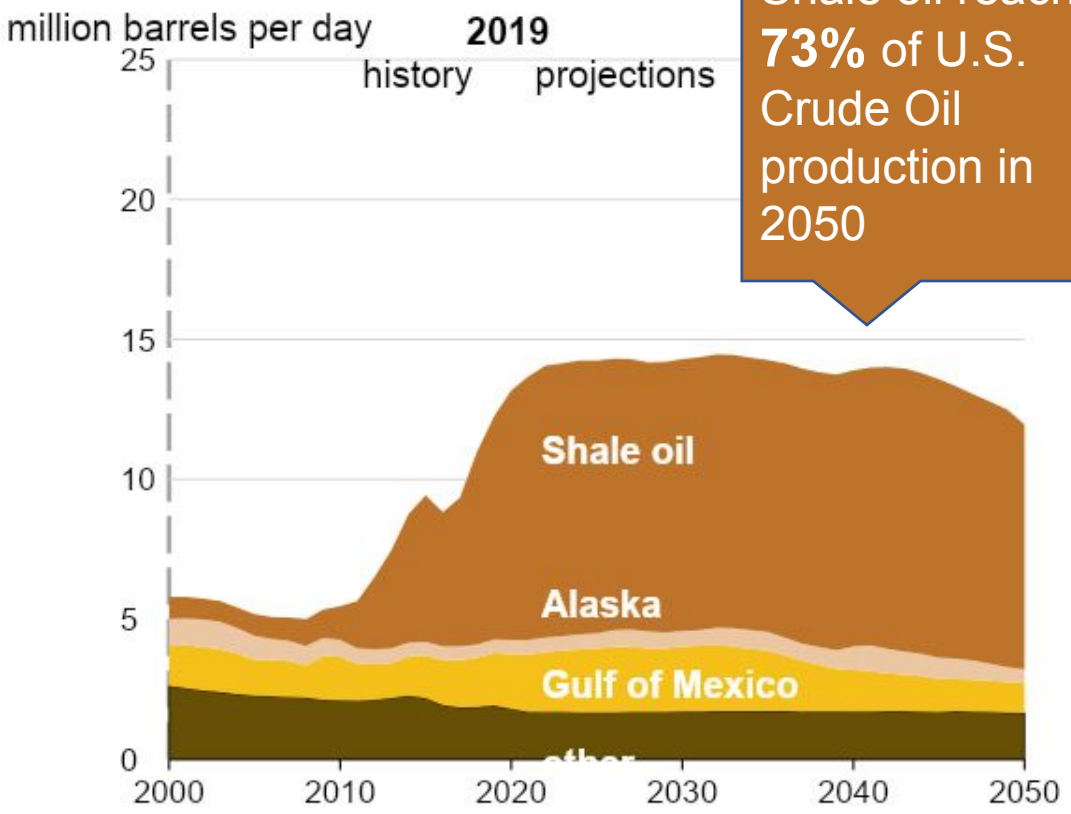
An **unconventional resource** is a fossil fuel energy extracted from **unconventional reservoirs**

Technology advancements have enabled **extraction** of **shale gas and oil**

Hydraulic fracturing and horizontal drilling has made extracting resources from shale reservoirs possible

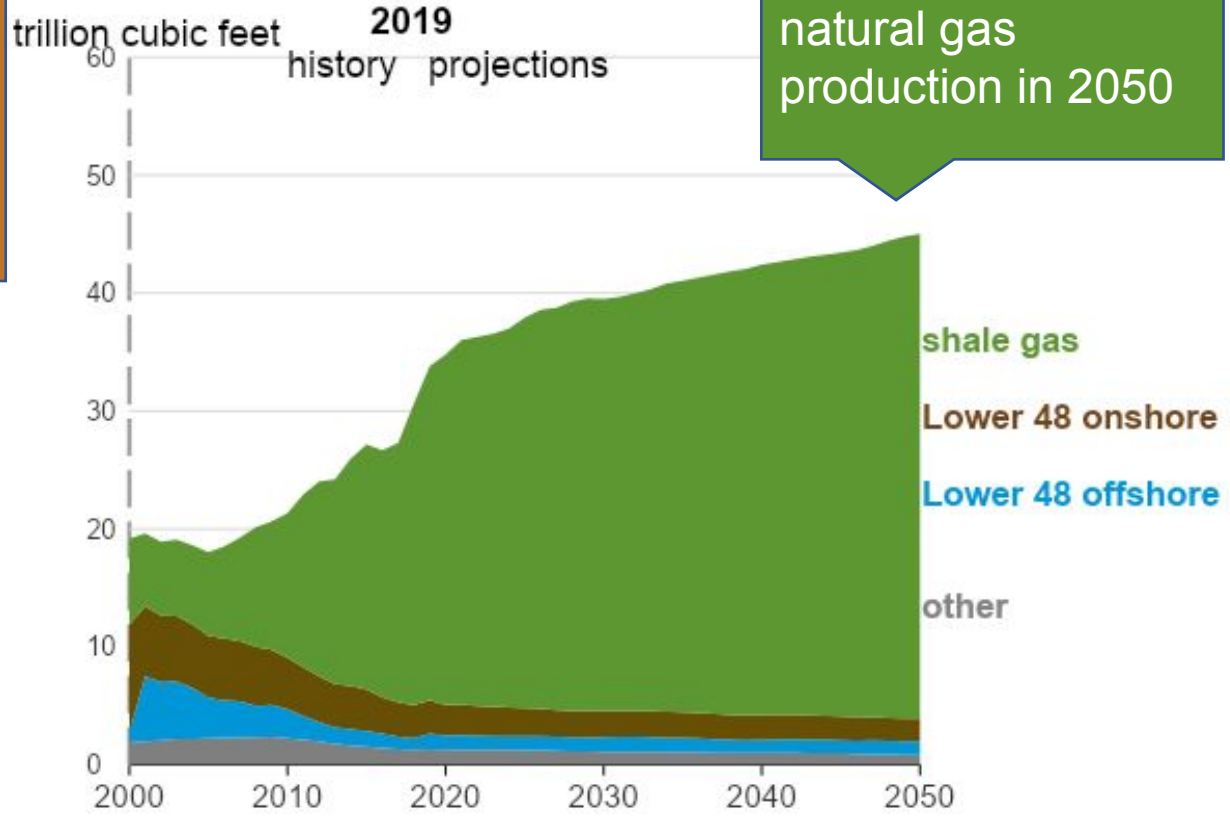
The United States continues to product historically high levels of…

Crude Oil



Shale oil reaches **73%** of U.S. Crude Oil production in 2050

Natural gas



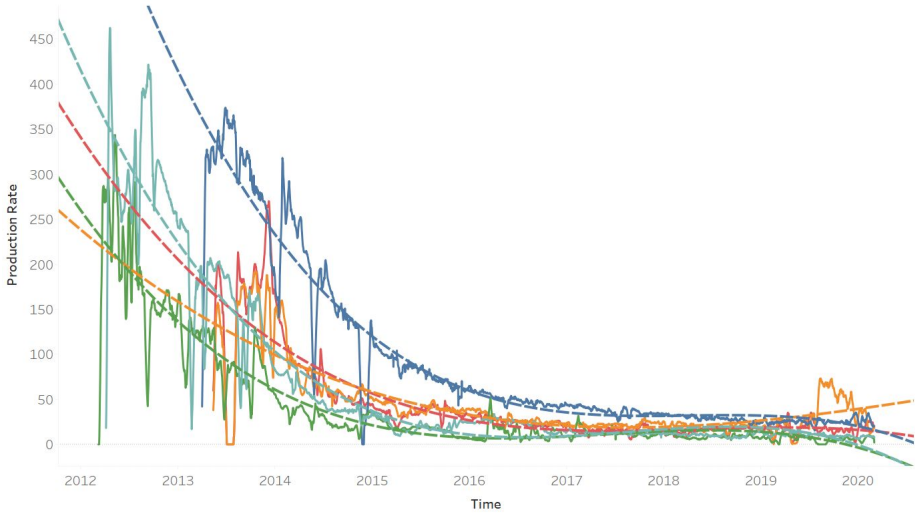
Shale gas reaches **91%** of domestic natural gas production in 2050

Data Source: U.S. Energy Information Administration, Annual Energy Outlook 2020 (AEO2020) Reference case

Production Forecasting: Current Industry Methods

(1) Decline Curve Analysis (DCA)

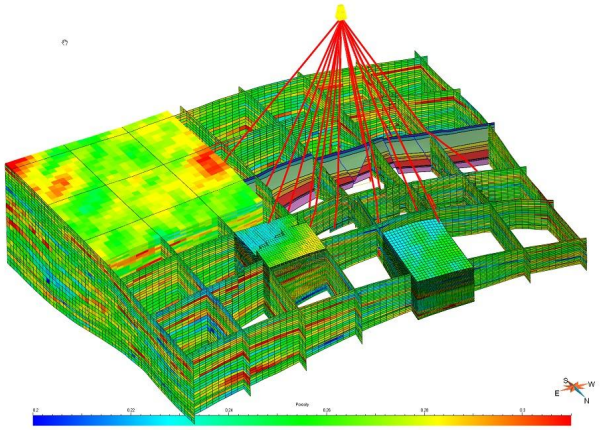
- "Empirical Method"
- Forecasting via graphical curve-fit procedure of historical data

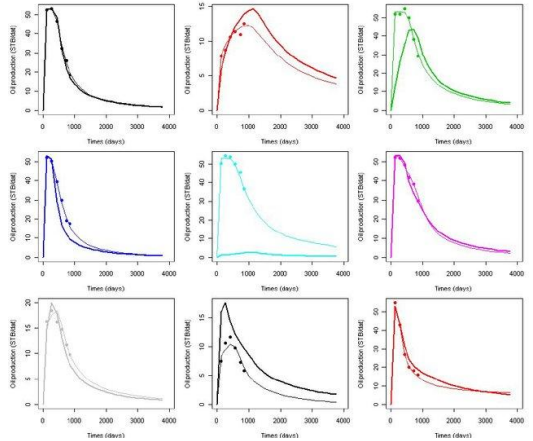


Fit equation through actual field data

(2) Reservoir Simulation

- "Analytical Method"
- Forecasting by simulating production data based on 3D modeling and simulation





3D Reservoir Model ➡ Simulate Production

Problem Overview

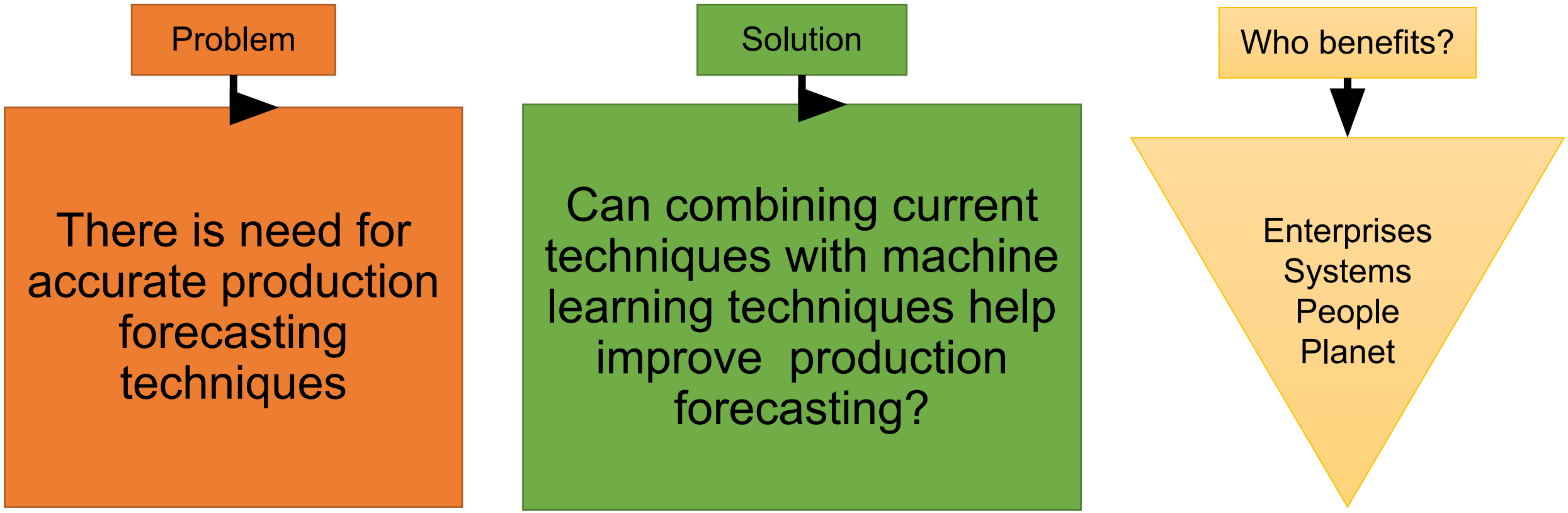
Decline Curve Analysis (DCA)

Model Development		Forecasting
Assumptions often misrepresent reality	→	Tendency to overestimate
Need rich historical production data in given area	→	Applicable for time-rate data only

Reservoir Simulation

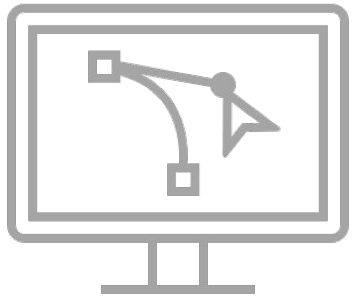
Model Development		Forecasting
Parameter uncertainty now in multiple dimensions	→	Inconsistent results
Complete measurements and expert interpretation	→	Computationally expensive

Thesis Problem Statement



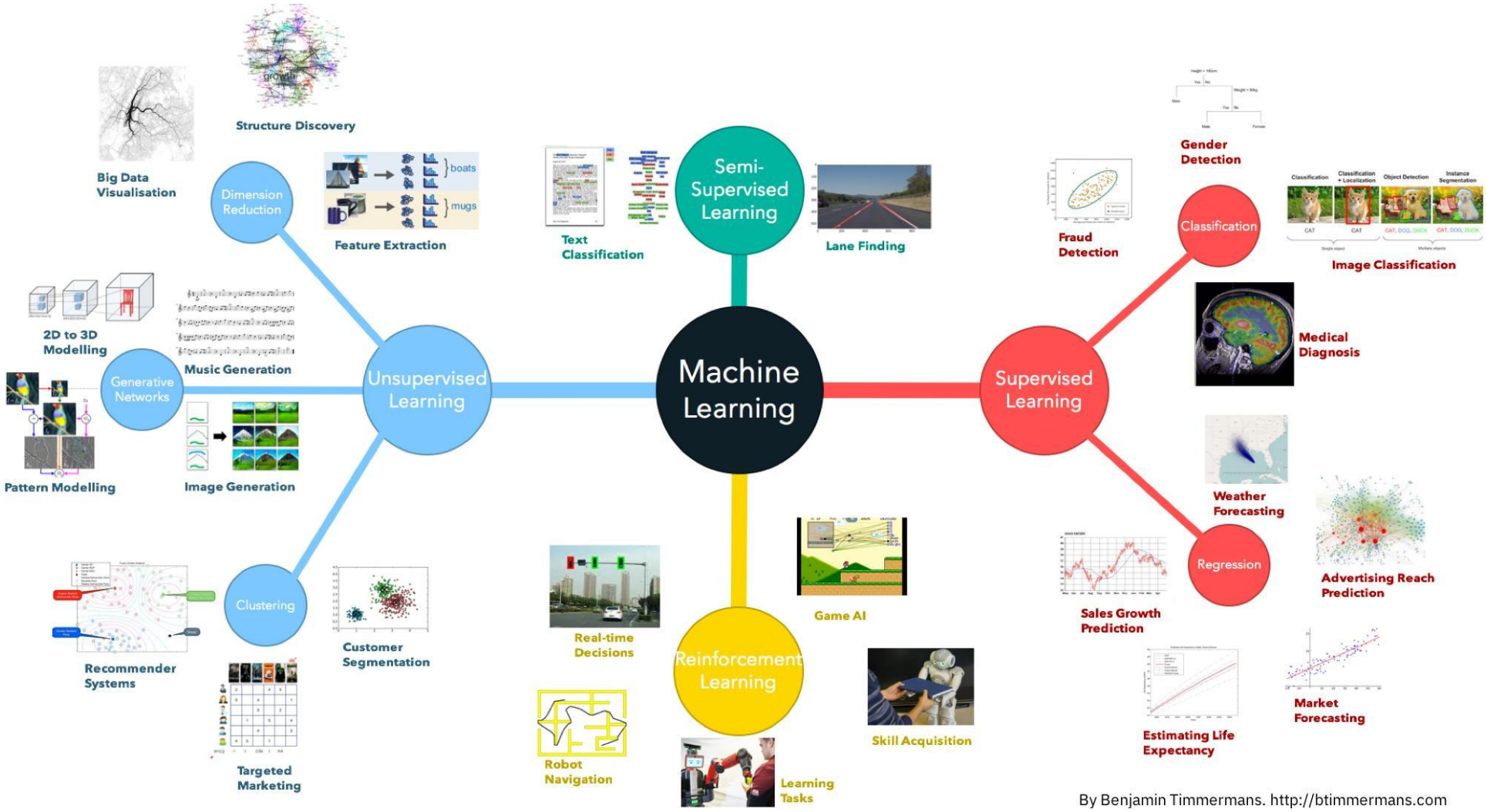
What is Machine Learning?

Human Learning: Improving at doing a task with experience



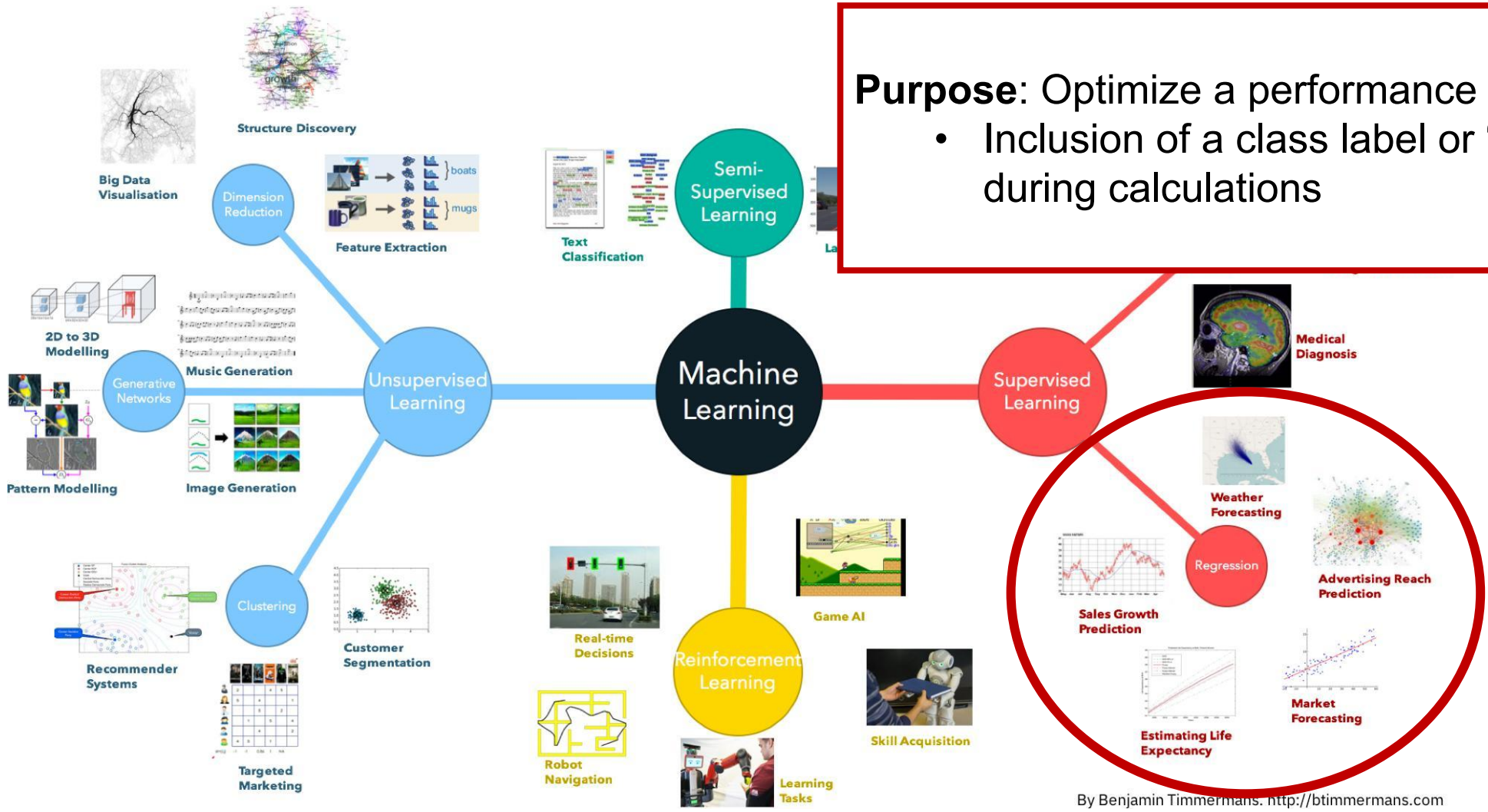
Machine Learning: Estimating parameters of a model so it best fits the dataset

What is Machine Learning?

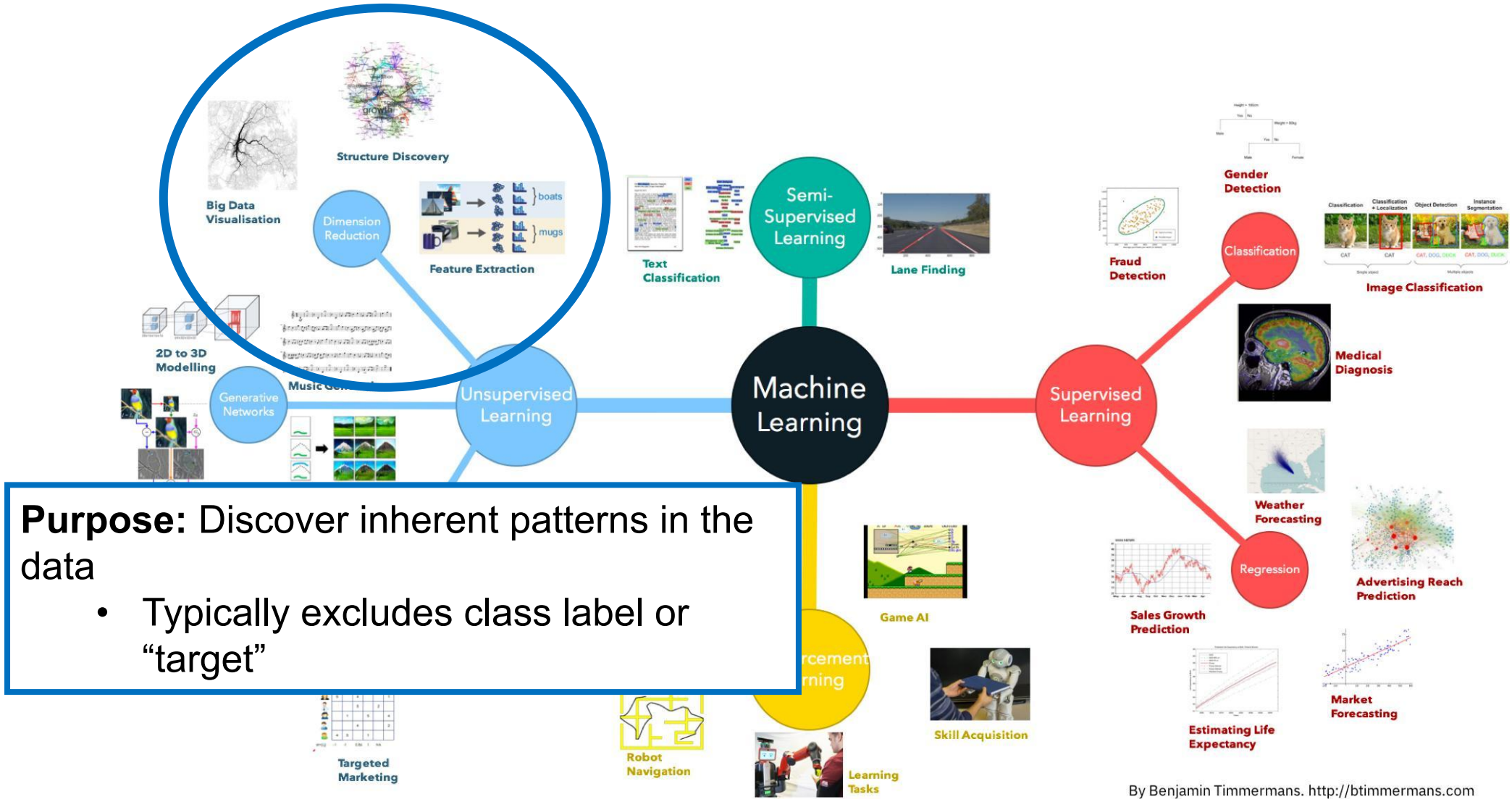


What is Machine Learning?

Purpose: Optimize a performance measure
- Inclusion of a class label or "target" during calculations



What is Machine Learning?



Purpose: Discover inherent patterns in the data

- Typically excludes class label or "target"

Supervised Learning: Linear Regression

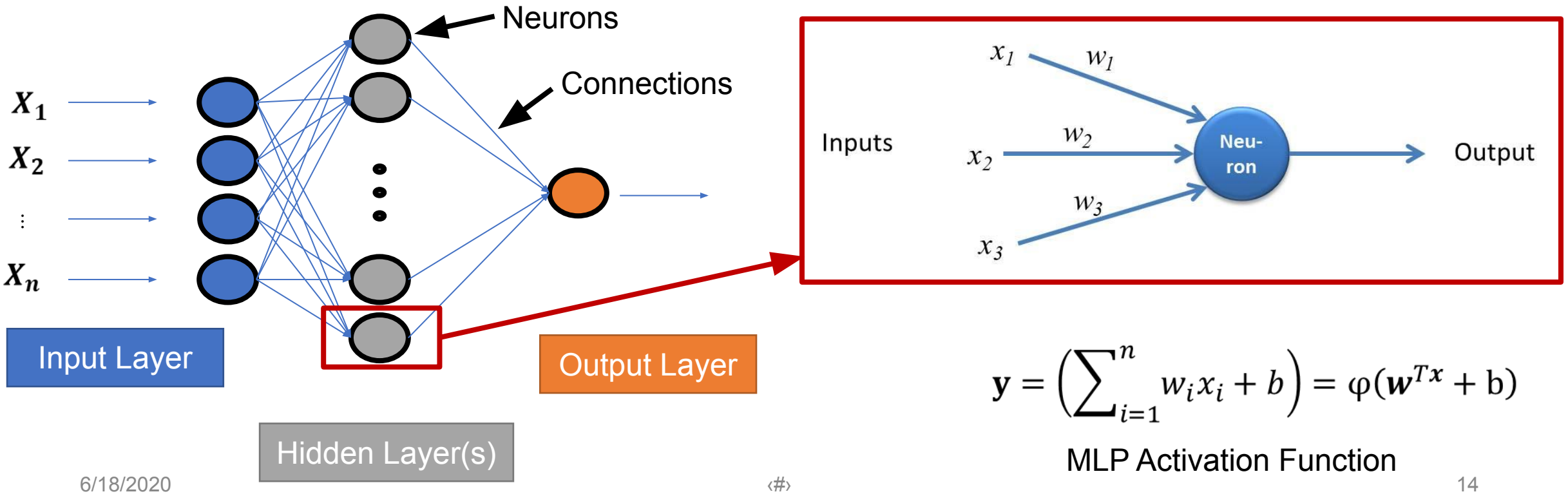
Linear Regression (LR)

- Fit set of predictor variables **X** to a target variable **Y** using linear predictor functions
- Estimate **β**s using the data
- Multivariate approach to production forecasting

$$\boldsymbol{Y} = \beta_0 + \beta_1 \boldsymbol{X_1} + \beta_2 \boldsymbol{X_2} + \cdots + \beta_n \boldsymbol{X_n}$$

Artificial Neural Networks (ANN)

- Experimental branch of science to simulate human learning
  - Multilayer Perceptron (MLP) most famous and widely used ANN
  - Nonlinear approach to production forecasting



$$\mathbf{y} = \left(\sum_{i=1}^{n} w_i x_i + b\right) = \varphi(\boldsymbol{w}^{T}\boldsymbol{x} + \mathrm{b})$$

MLP Activation Function

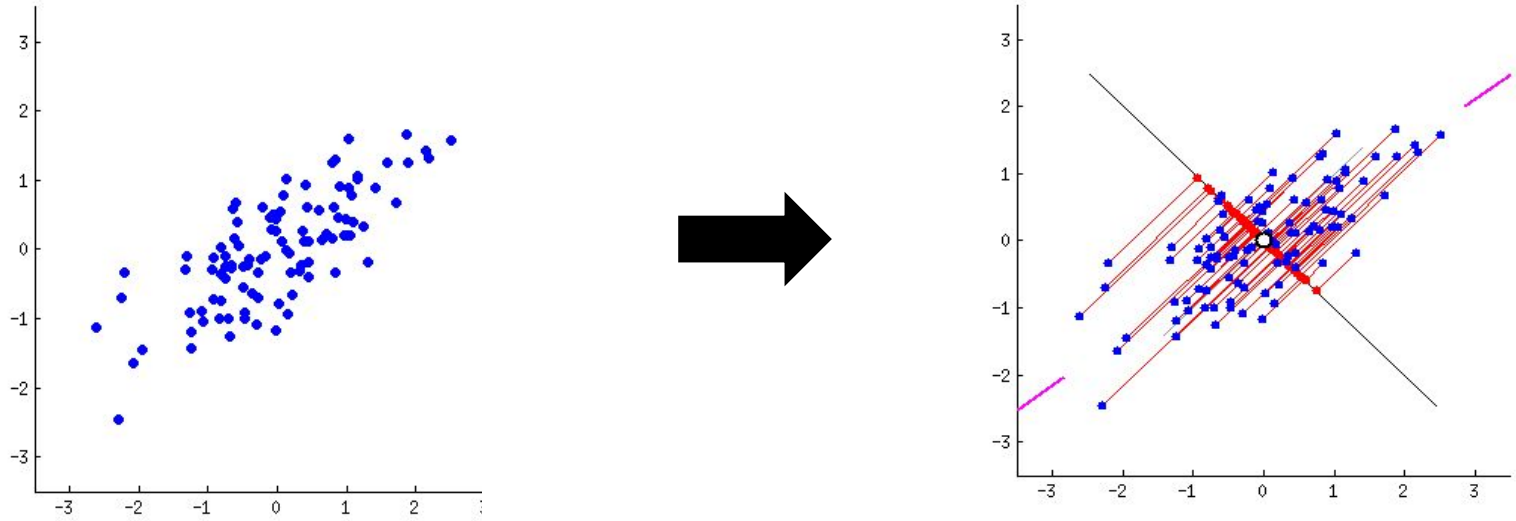
Unsupervised Learning via Dimension Reduction

- Represent the data with fewer dimensions
  - Retain the most statistical variance possible
  - More tractable subset of original data, easier for learning
  - Discover intrinsic patterns in the data

  - *Feature selection* = creating a **subset** of the original feature set
  - *Feature extraction* = creating a **new set** of features from the original feature set.

Feature Extraction via Principal Components Analysis (PCA)

- PCA is dimension reduction technique that maps original data onto a *linear subspace,* such that the retained statistical variance of the projected data is maximized

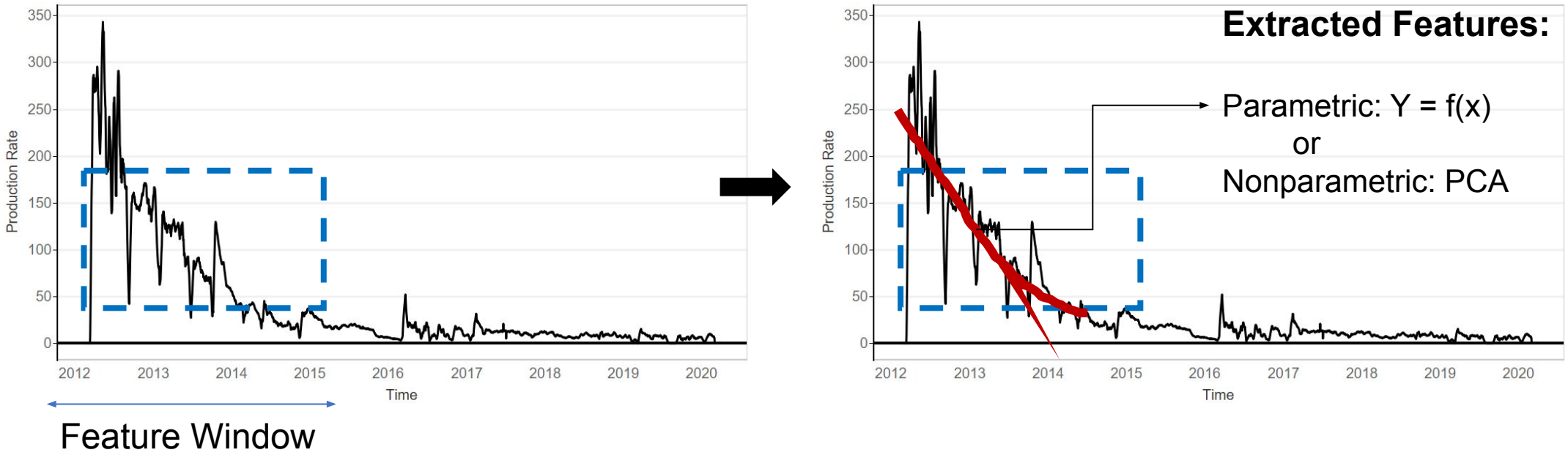


- The principal components (PCs) represent a **new subset** of the data

Feature Extraction of Time-Series

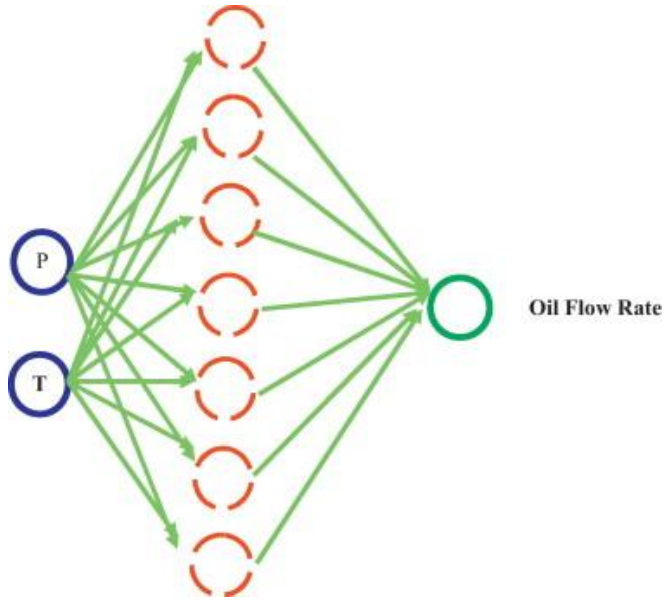
Decompose time-series into components that represent some pattern of the series

- (1) understand time series patterns (2) forecast new values
- Parametrically via curve-fitting
- Nonparametrically via PCA

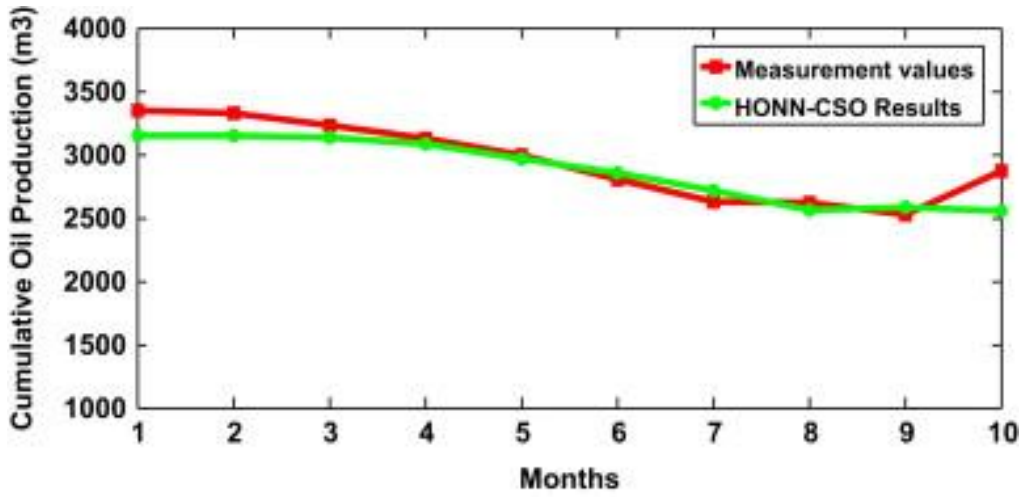


Literature Review

Literature Review: ANN in Oil/Gas Industry



Ahmadi and Ebadi (2017) used pressure (P) and temperature (T) data as inputs to MLP to predict oil flow rates



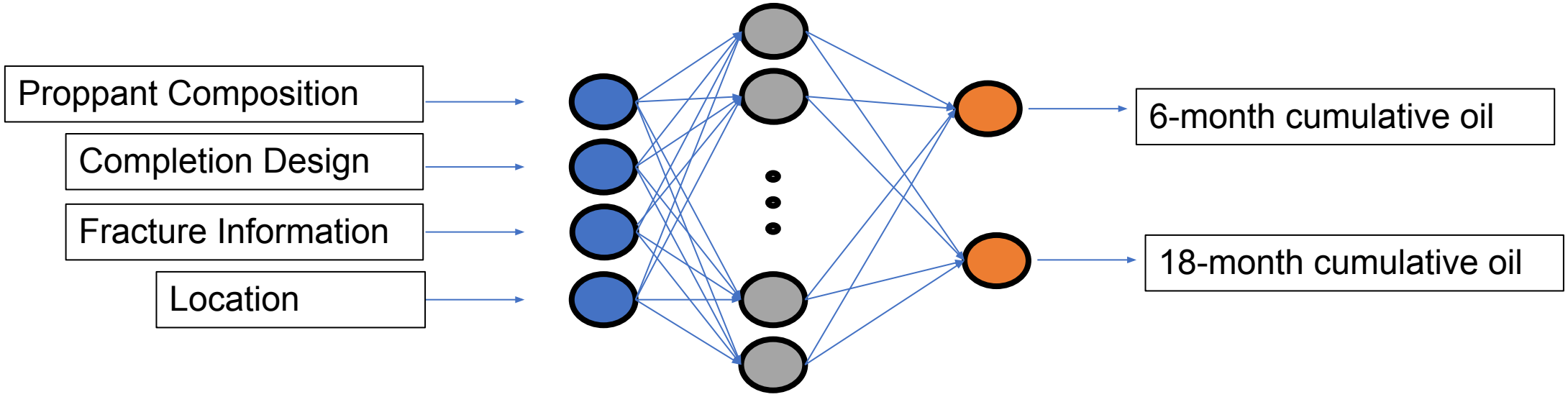
Chakra and Song (2013) applied an ANN (HONN-CSO) using correlation matrix of oil, gas, and water data as inputs to predict 10-month cumulative oil production

- Production yielded < 4.0% error
- Did not incorporate static well parameters

Literature Review: ANN in Oil/Gas Industry

Wang and Chen (2019)

- Applied MLP to predict cumulative oil production in Bakken Shales
- Test set R^2 71% and 72% for 6- and 18-month cumulative oil



Luo and Tian (2019)

- Compared LR and MLP to predict first 6-months cumulative oil
- Measured depth, TVD, fluid, and proppant to be most important variables

Literature Review: PCA in Oil/Gas Industry

- Reconstructing production profiles with FPCA (Bhattacharya and Nikolaou, 2013)
  - Sum products of PCs and associated scores and add each sum to the mean function computed on entire ensemble

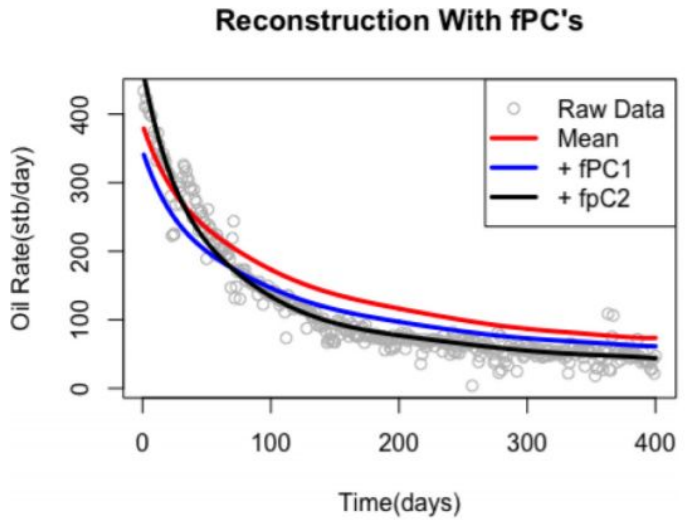
Inputs

Static Data
- Completions
- Geographical
- PVT
- Petrophysical

Predict

Outputs

Production Data
- Oil Rates
- Gas Rates
- Water Rates



Literature Review: PCA in Oil/Gas Industry

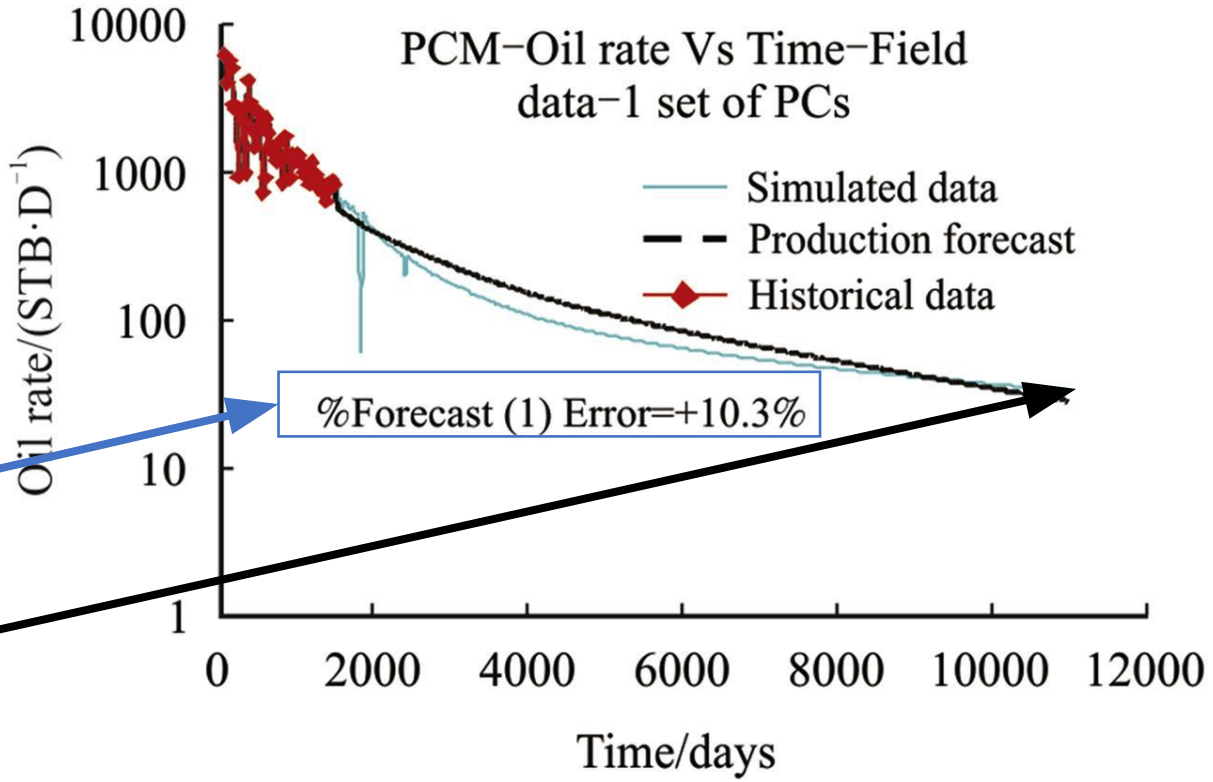
- Makinde and Lee (2019)
  - Feature extraction .5 to 3 years of production data for forecasting 30 years time-horizon

Profile Reconstruction using .5 to 3 years of data (Bhattacharya and Nikolaou, 2013)

Evaluate PCA reconstruction

Forecast 30 years

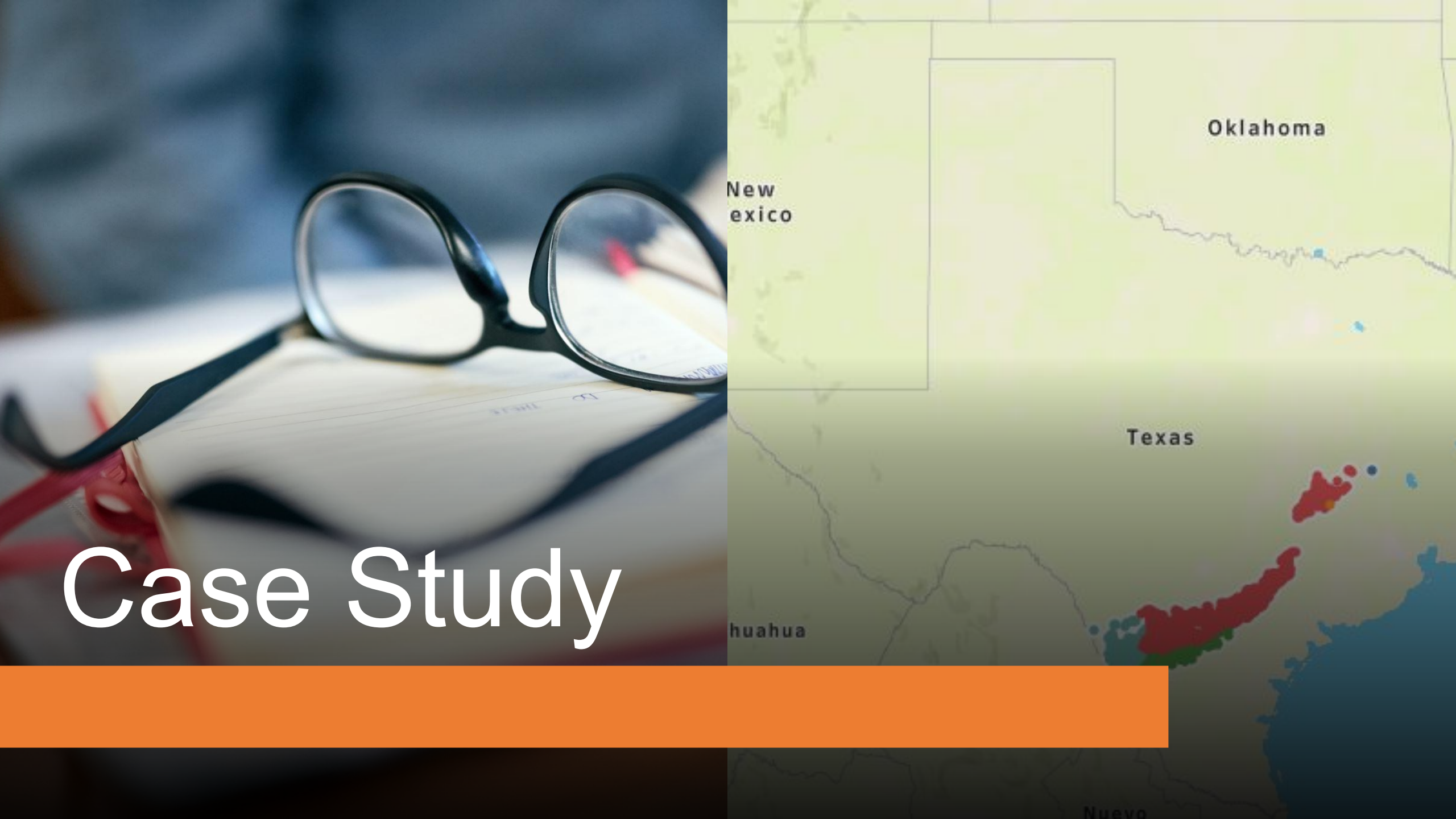
Compare to simulated data



Study Goal and Objectives

- Study Goal
  - *Create multivariate well-proxy model that incorporates both static and dynamic variables to predict cumulative oil production*

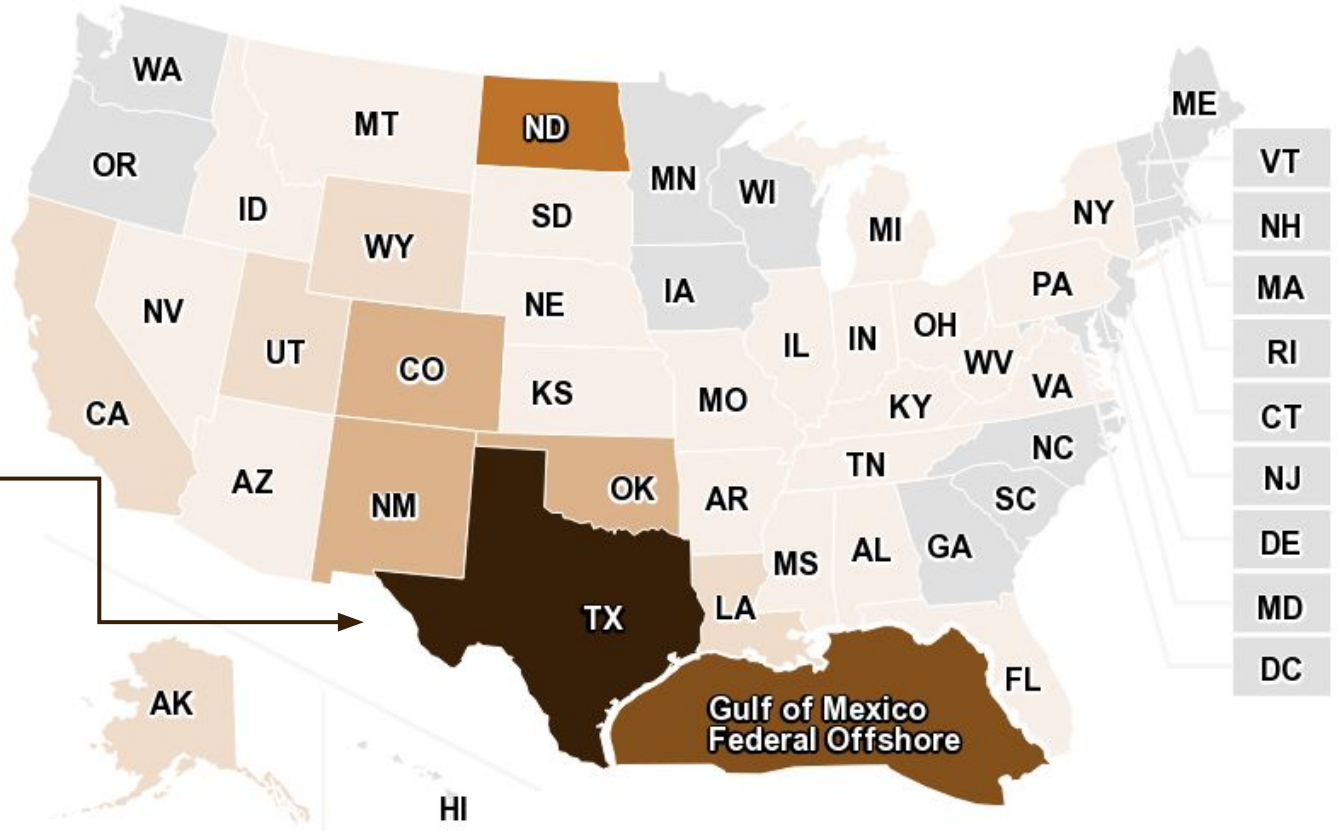
- Main Purposes
  1) Determine if regression-based predictions using **parametric** and **nonparametric** feature extraction could predict cumulative oil
  2) Determine efficacy of including static well variables into modeling
  3) Determine if model complexity aids prediction results



Case Study

Texas Oil

41% of U.S Crude Oil produced in 2019 came from Texas

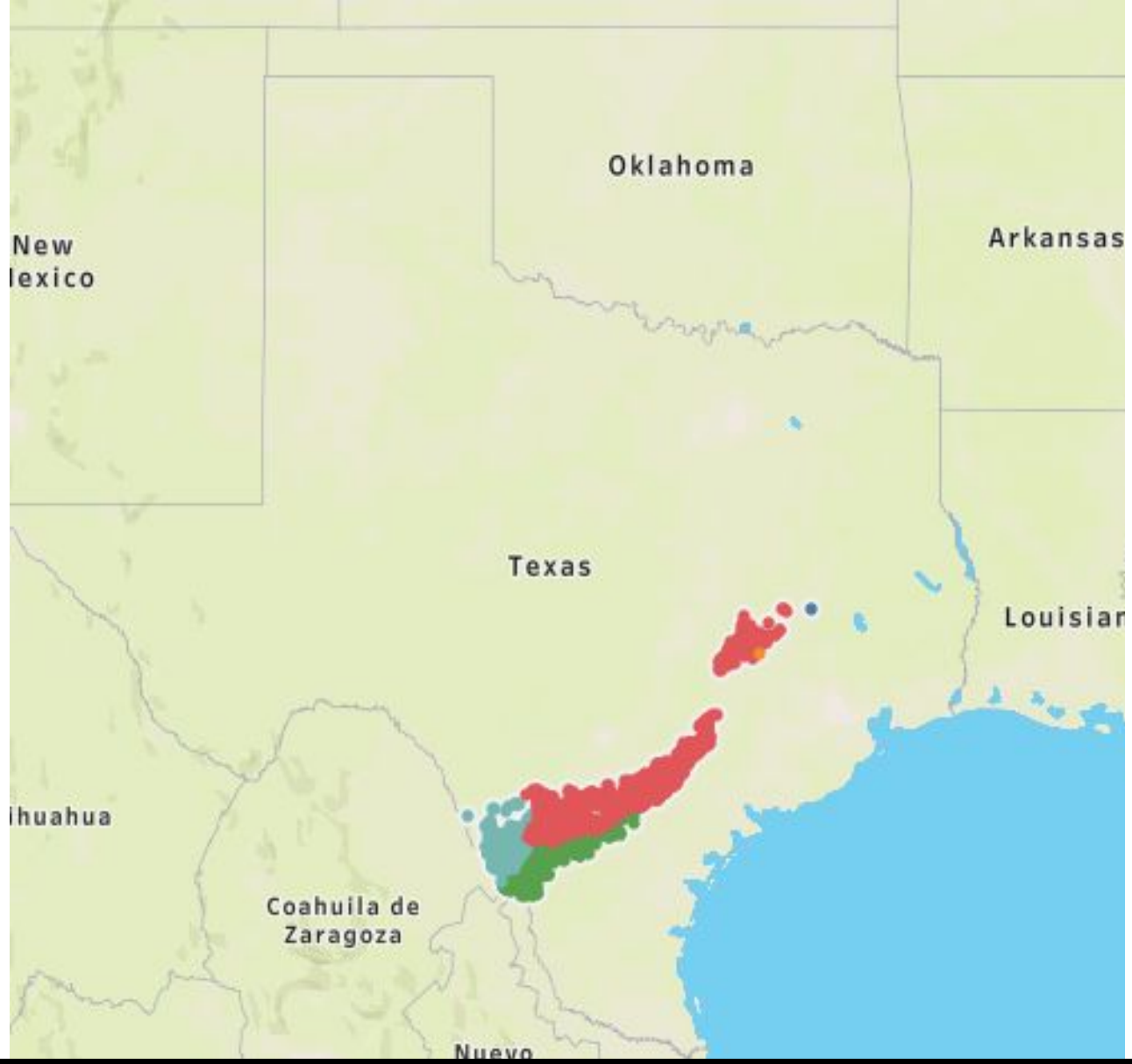


= 0 | < 100 | 100 - 500 | 500 - 1000 | 1000 - 1500 | 1500 - 2000 | > 2000

Note: Crude oil incudes lease condensate.
Source: U.S. Energy Information Administration, *Petroleum Supply Monthly*, February 2020, preliminary data

The Eagle Ford Shale

- $60 billion impact since initial development in 2006
- Production Forecasting Challenge
  - Limited production history
  - Unique areal variation



Case Study Overview

Data from 448 oil wells in EFS

- *Dynamic p*roduction Data
  - Time-series oil, gas, water production
- *Static* well Information
  - Well design measurements, locational, PVT data.

Scenarios for input data

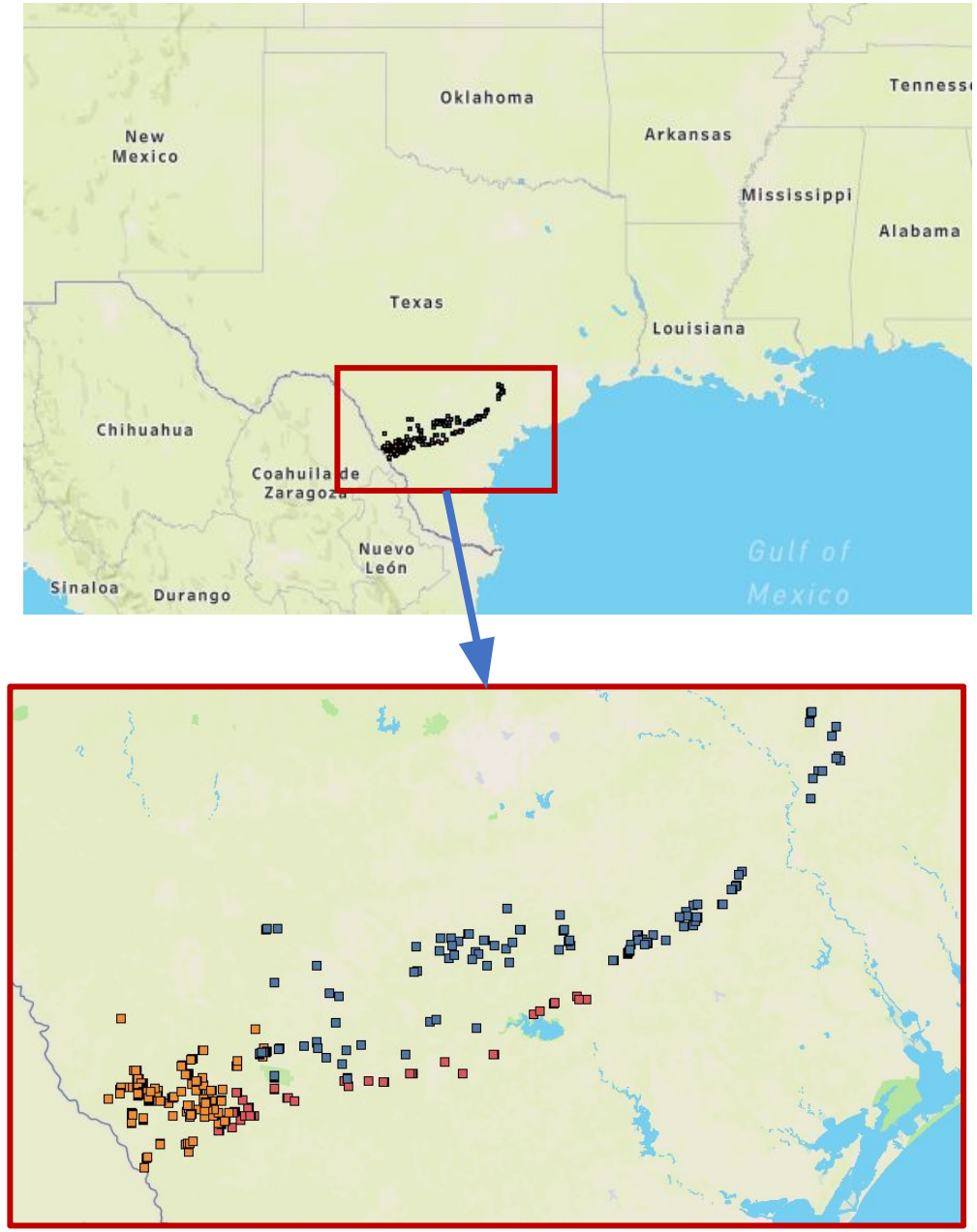
(1) 6-months

(2) 12-months

(3) 24-months

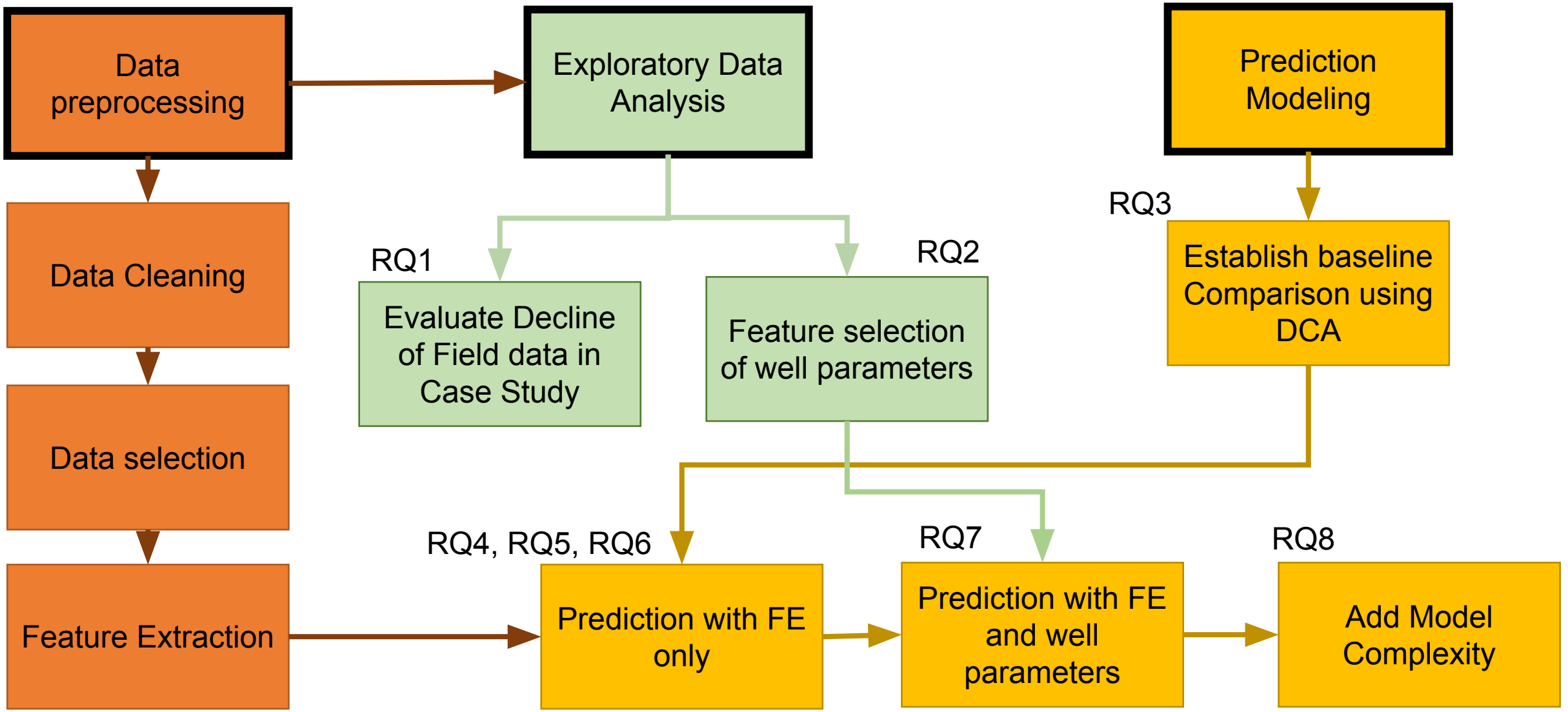
Target variable of interest

- three-year oil cumulative oil

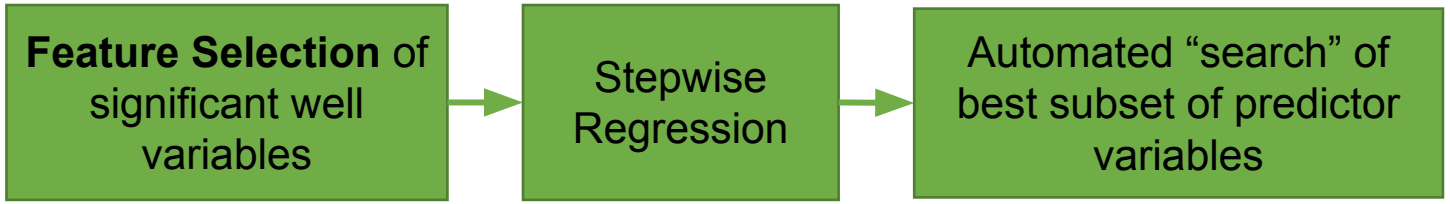


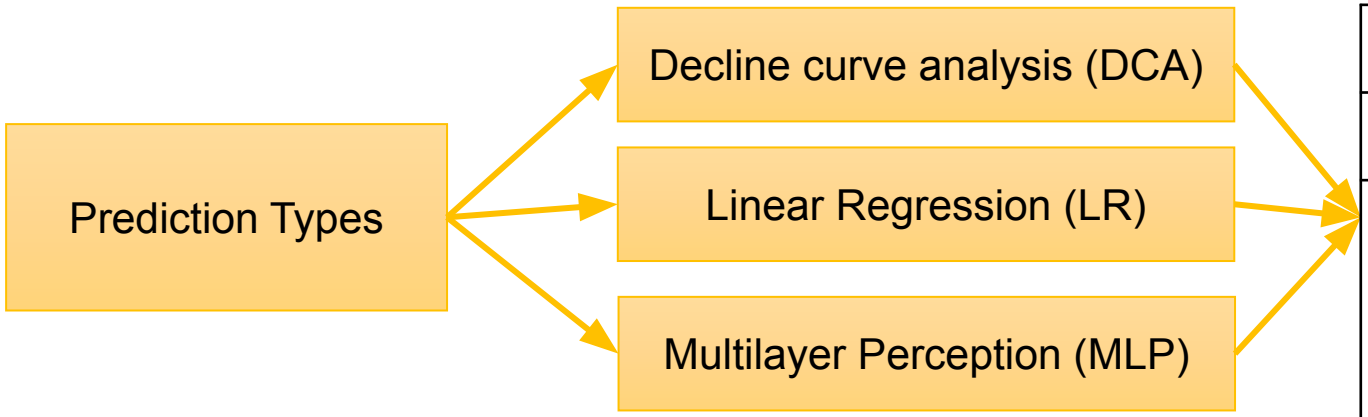
Research Framework

*FE = Feature Extraction
*DCA = decline curve analysis



Design of Experiments Overview

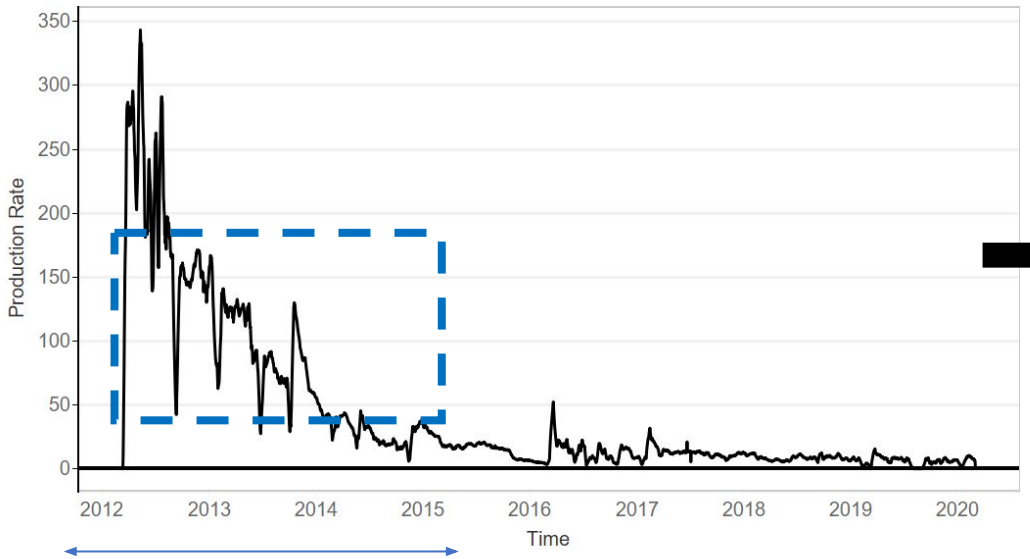




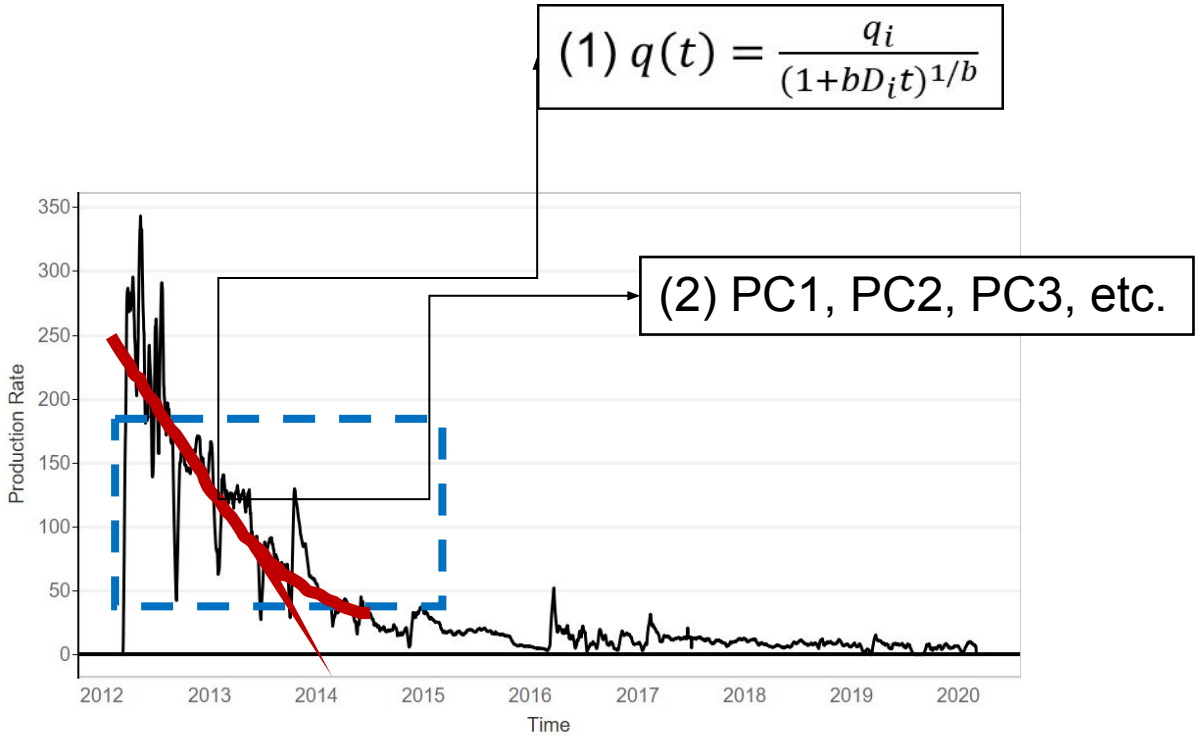
Evaluation Metrics		
RMSE	**MAPE**	**R^2**
Weight on magnitude of Errors	*Weight on repetition of errors*	*Proportion of variance explained by model*

Feature Extraction Methods: A quick review

(1) Arps : optimal q_i, b, D_i parameters
(2) PCA: principal components of water, gas, oil data
(3) Hybrid: combine Arps + PCA



Feature Window

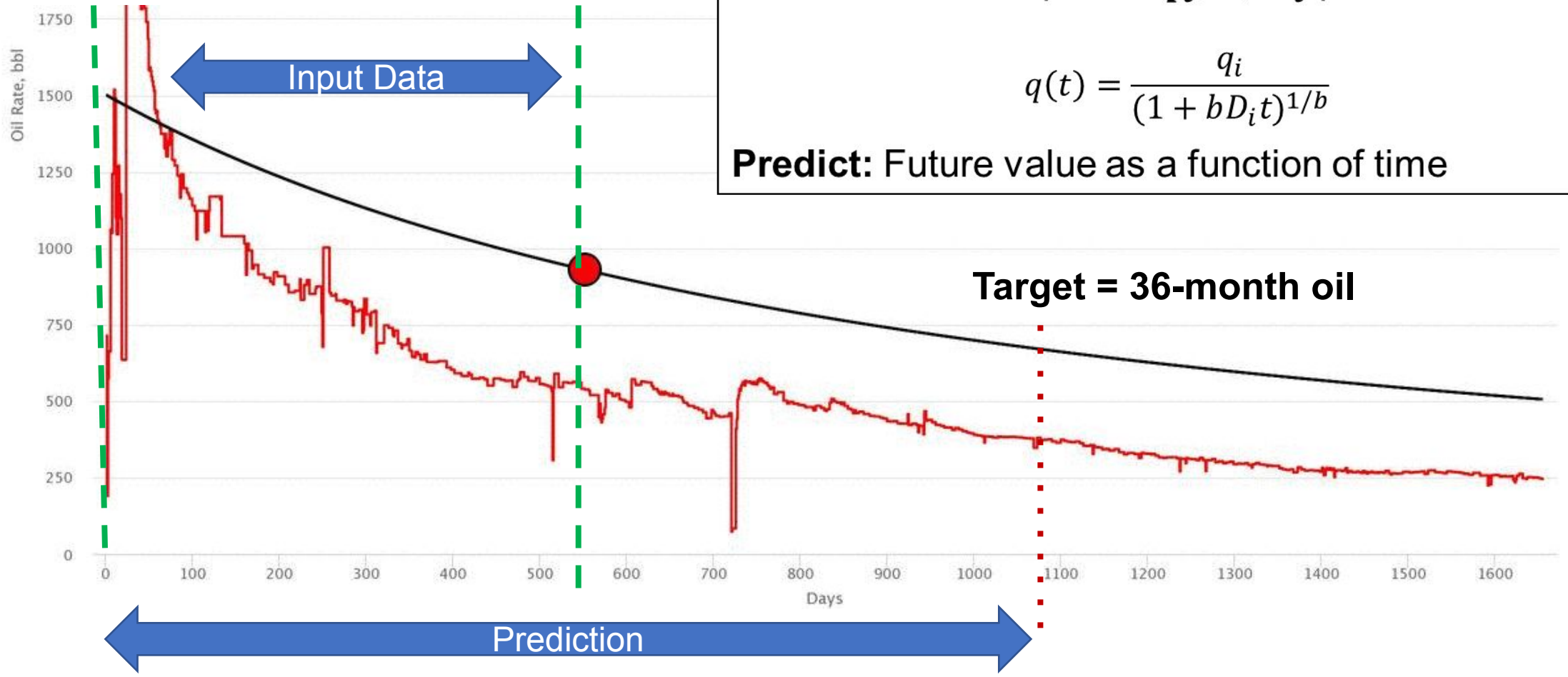


Prediction Type 1: Decline Curve Analysis (DCA)

How: Determine optimal q_i, b, D_i parameters

$$q(t) = \frac{q_i}{(1 + bD_i t)^{1/b}}$$

Predict: Future value as a function of time



Prediction Type 2: Linear Regression

Linear Regression using extracted features as predictor variables

RQ4: parametric $\mathbf{Y} = \beta_0 + \beta_1 \mathbf{q_i} + \beta_2 \mathbf{b} + \beta_n \mathbf{d_i}$

RQ5: nonparametric $\mathbf{Y} = \beta_0 + \beta_1 \mathbf{PC_1} + \beta_2 \mathbf{PC_2} + \cdots + \beta_n \mathbf{PC_R}$

RQ6: hybrid $\mathbf{Y} = \beta_0 + \beta_1 \mathbf{q_i} + \beta_2 \mathbf{b} + \beta_3 \mathbf{d_i} + \beta_4 \mathbf{PC1} + \beta_5 \mathbf{PC2} + \ldots + \beta_n \mathbf{PC_R}$

**Compare these results with DCA from RQ3*

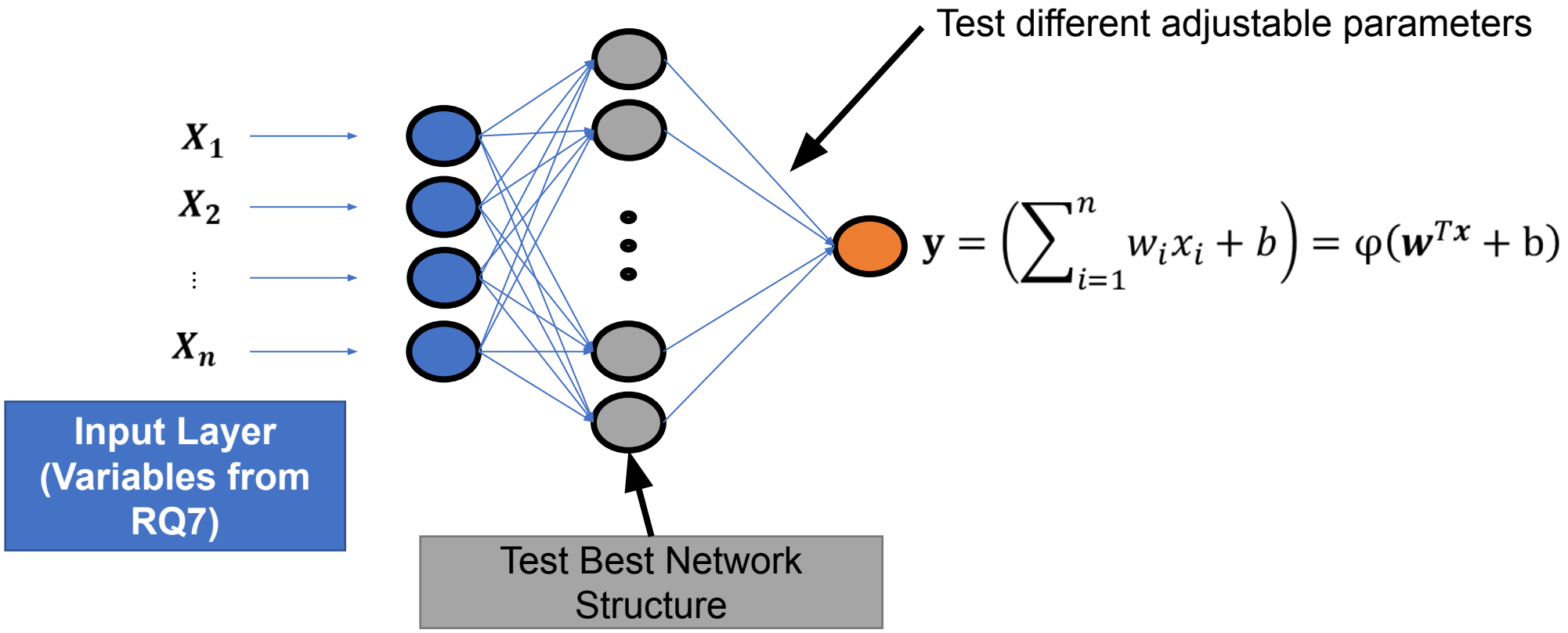
RQ7: Linear Regression using extracted features (FE) + static well features

RQ7: $\mathbf{Y} = \beta_0 + \beta_1 \boldsymbol{FE_1} + \beta_2 \boldsymbol{FE_2} + \cdots + \beta_n \boldsymbol{X_1} + \beta_{n+1} \boldsymbol{X_2} + \cdots + \beta_k \boldsymbol{X_k}$

Prediction Type 3: MLP

RQ8: Adding model complexity through MLP using existing input variables as RQ7

**Compare results with RQ7*

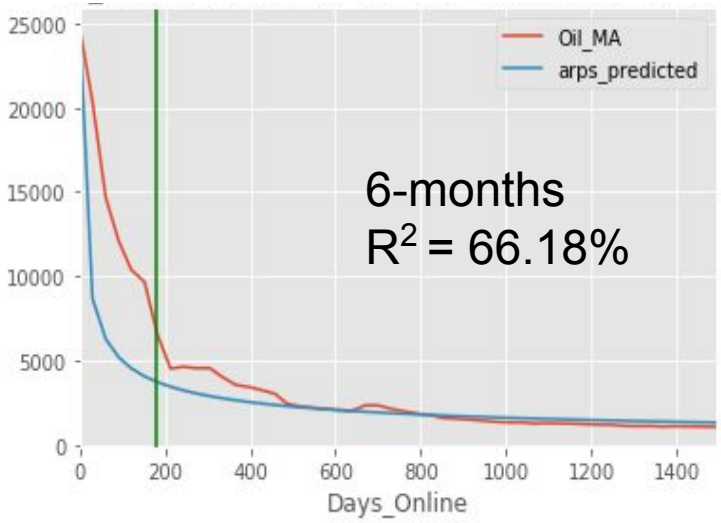


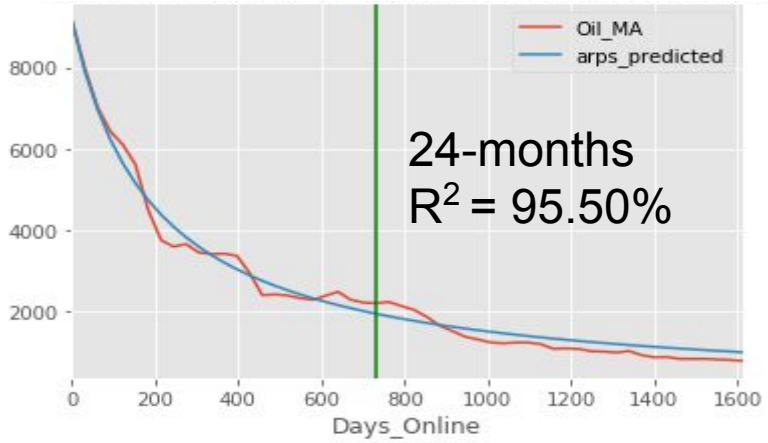
Results: Evaluating Arps Model

Answering research question RQ1

Goodness-of-fit metrics using Arps Model

Scenario	RMSE	MAPE	R^2
6 Months	14253	16.26%	66.18%
12 Months	4989	8.53%	91.63%
24 Months	3659	6.31%	95.50%





Results: Feature Selection of Static Well Variables

Answering research question RQ2

Parameter Type	Parameter	Rank
PVT	Oil Gravity	1
Completion	True Vertical Depth	2
Location	Surface Latitude	3
Location	BH Longitude	4
Completion	Proppant to Fluid Ratio	5
Completion	CLL	6
Completion	Total Fluid	7

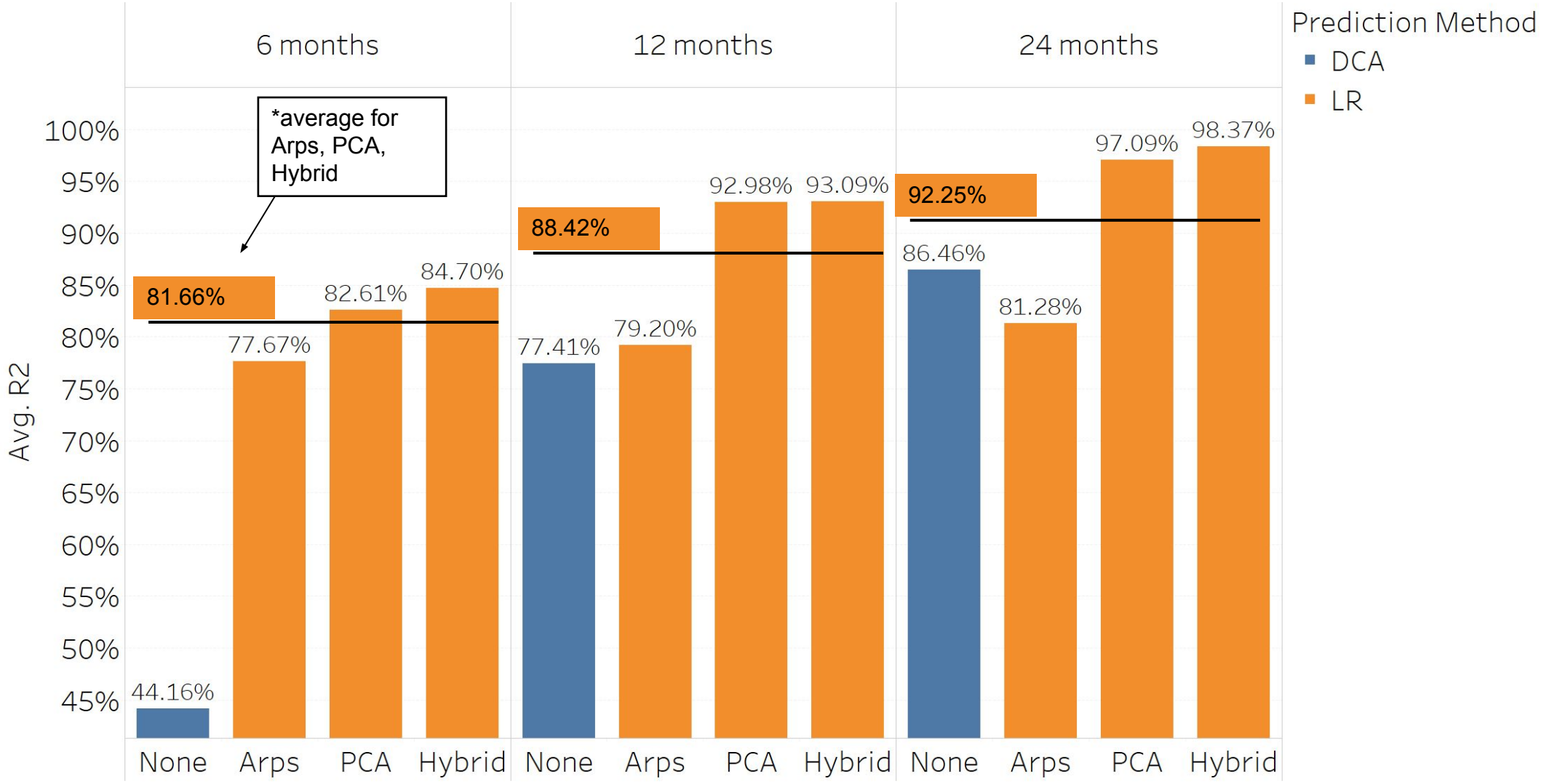
RMSE	MAPE	R^2
80942	21.18%	**52.11%**

Summary

- Three types of well variables were found significant
- 51.11% proportion of variance explained by regression model

Results: Can regression prediction outperform DCA?

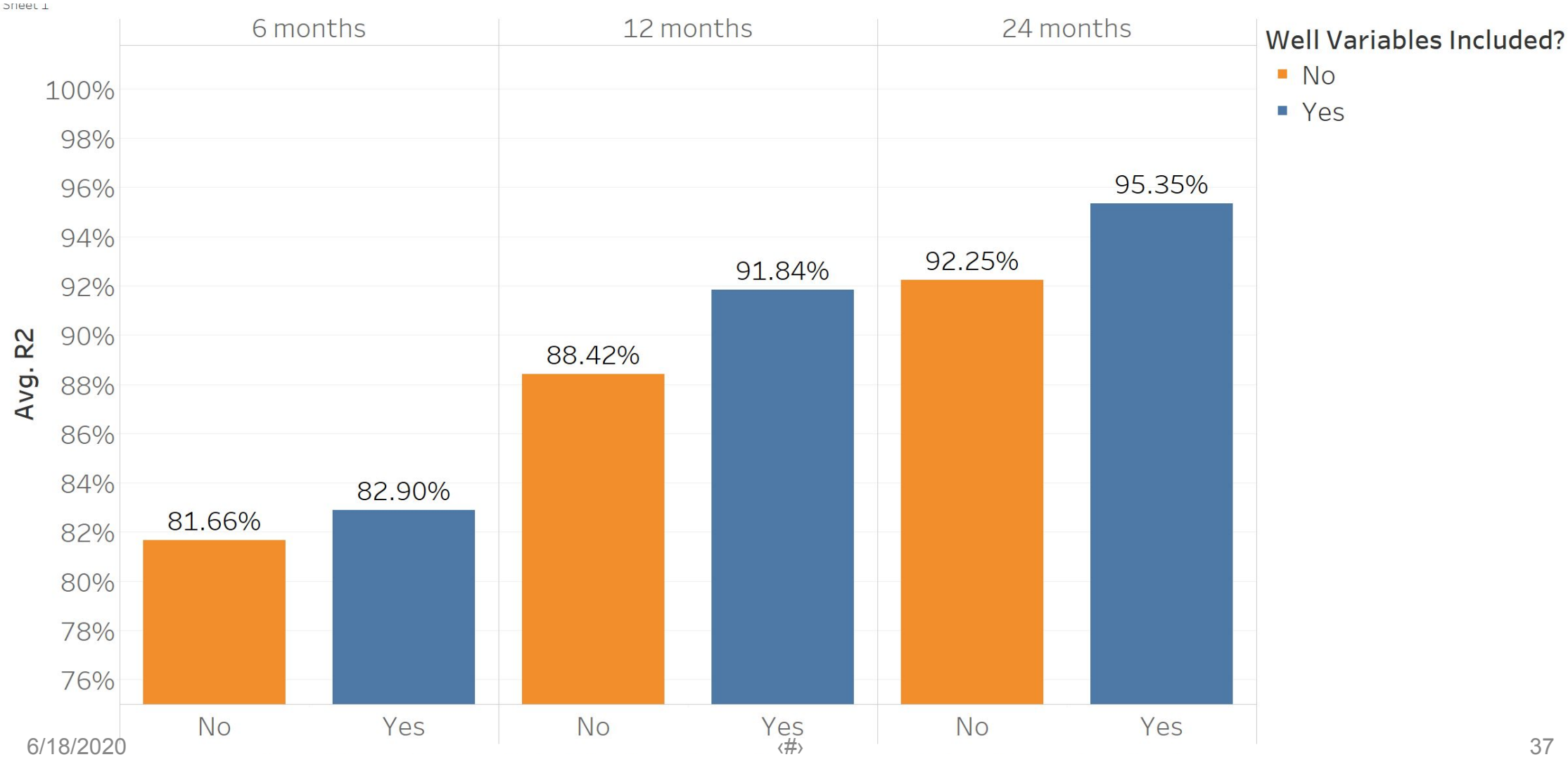
Answering Research Questions RQ3 – RQ6



Results: Does Including Well Variables Aid the prediction?

Answers Research Question RQ7

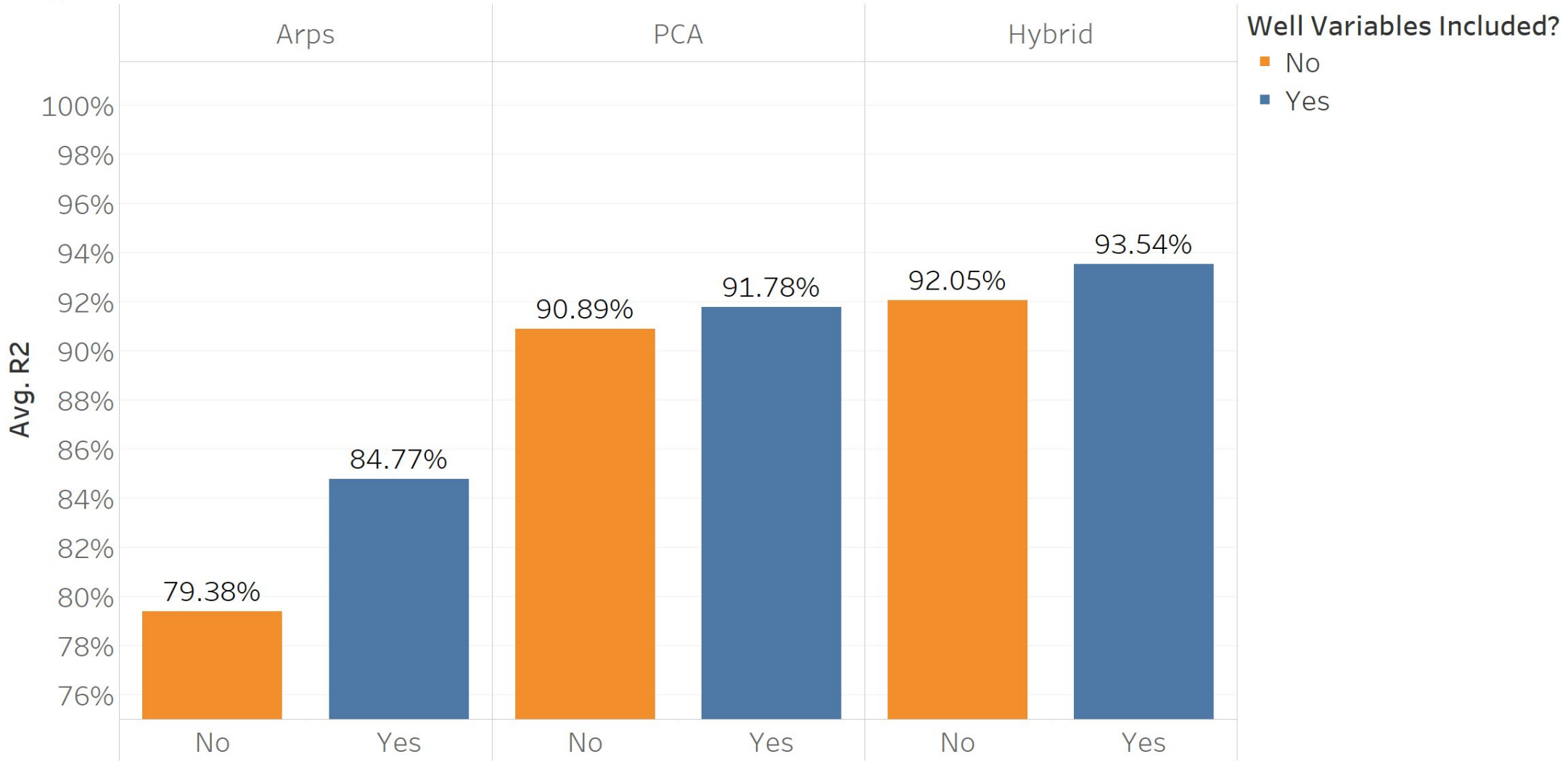
Average R^2 by prediction scenario when well variables included in the model



Results: Does Including Well Variables Aid the prediction?

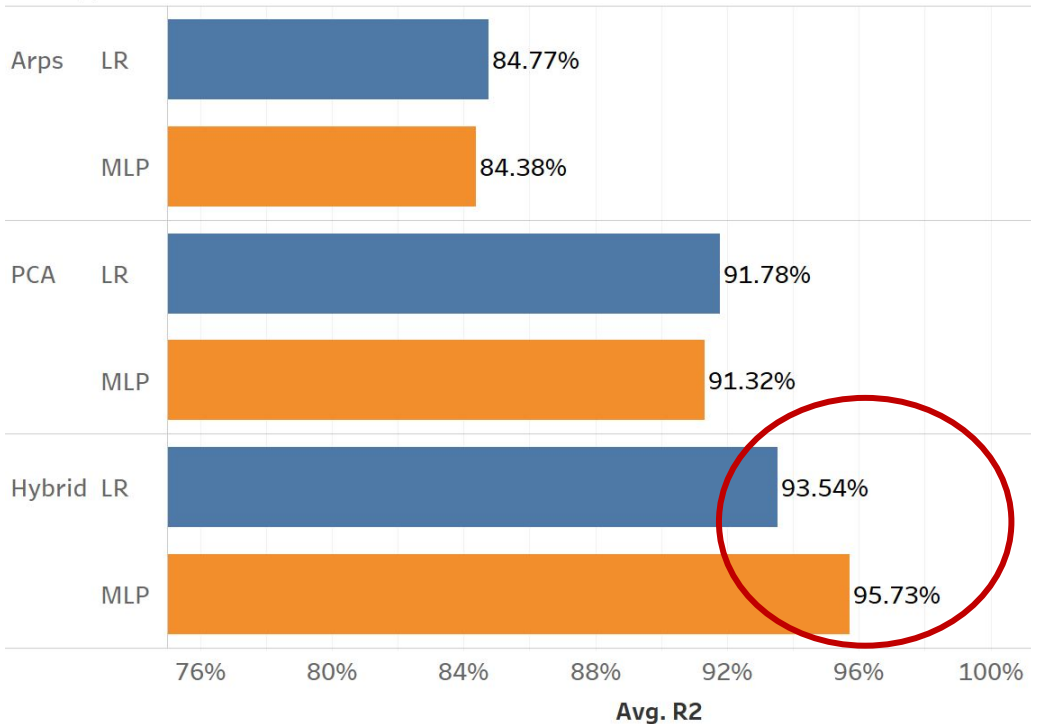
Answers Research Question RQ7

Average R^2 by feature extraction method when well variables included in the model



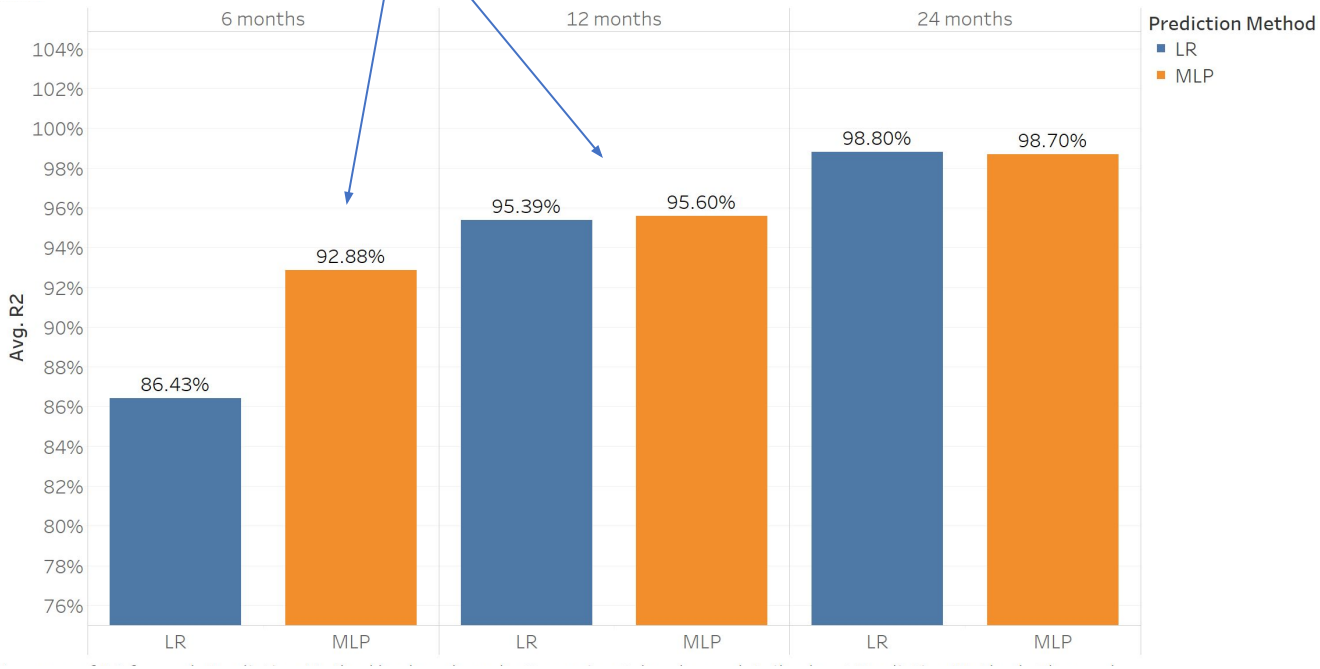
Results: Does adding model complexity aid the prediction results?

Answers research question RQ8



Average across all data scenarios reveals *Hybrid* as best feature extraction

Recall: 24-month DCA method yielded 86.46% R^2



Comparison of hybrid methods only

Conclusions

Research Contributions, Study Limitations, Future Work

Conclusions and Contributions

- **Regression using feature extraction** is more effective than DCA
  - PCA of production data was effective in explaining statistical variance
  - Combination of DCA and PCA most effective in prediction

- **Inclusion of static well variables** can make valuable predictions about future cumulative oil production
  - Improved regression prediction results for all scenarios

- **Model complexity** not needed when richer production history available
  - Valuable in case of 6-months of data; predicted better with less data than DCA

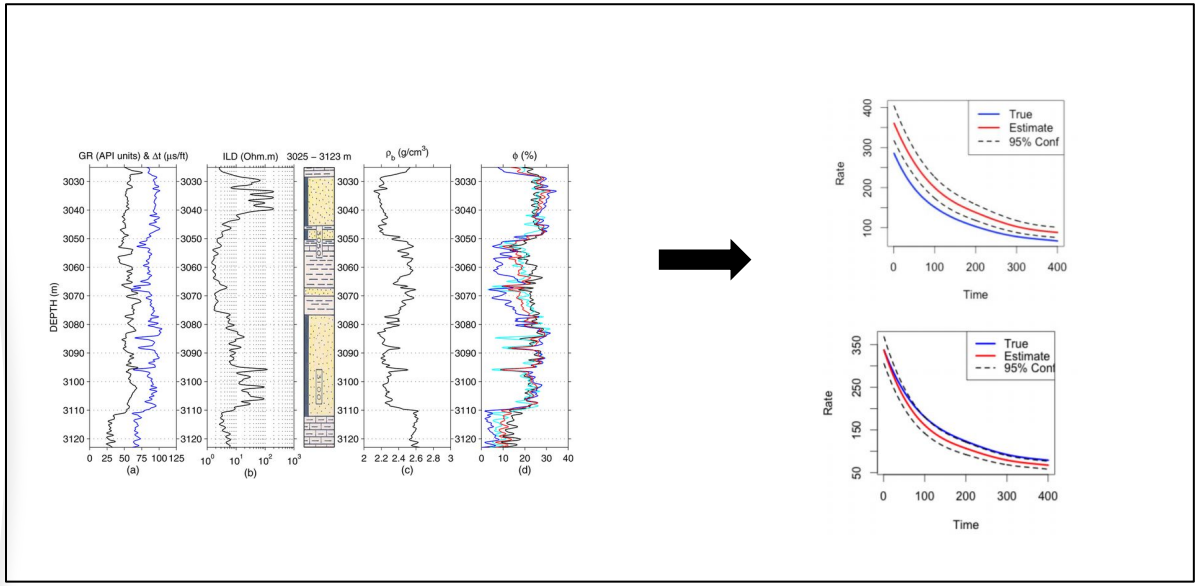
Future Work

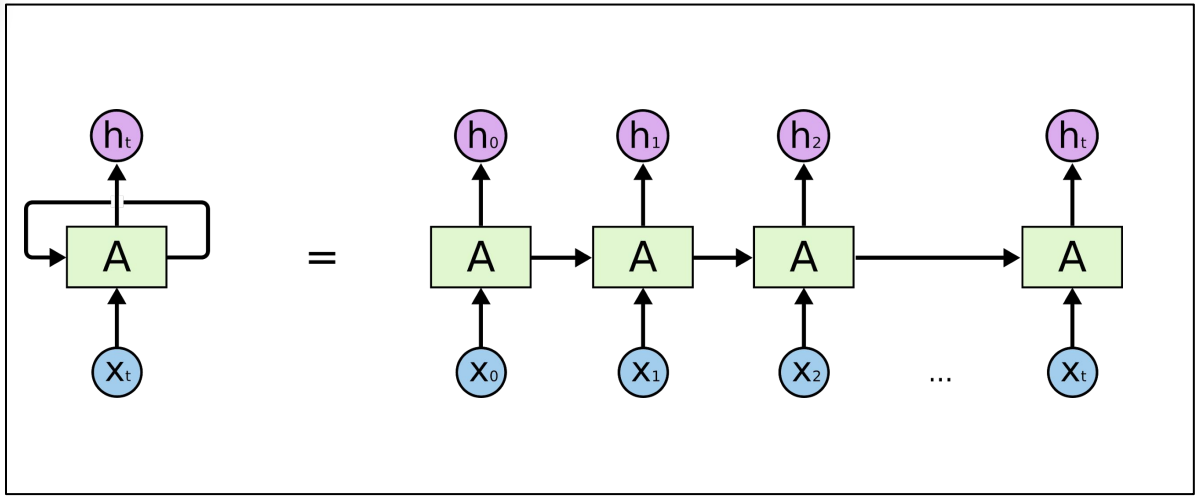
Include richer data

- Geologic, well logs, seismic, and reservoir pressures
- Multivariate prediction

New Prediction Scenarios

- Time-series neural network for month-to-month rate prediction
- Estimated Ultimate Recovery (EUR)



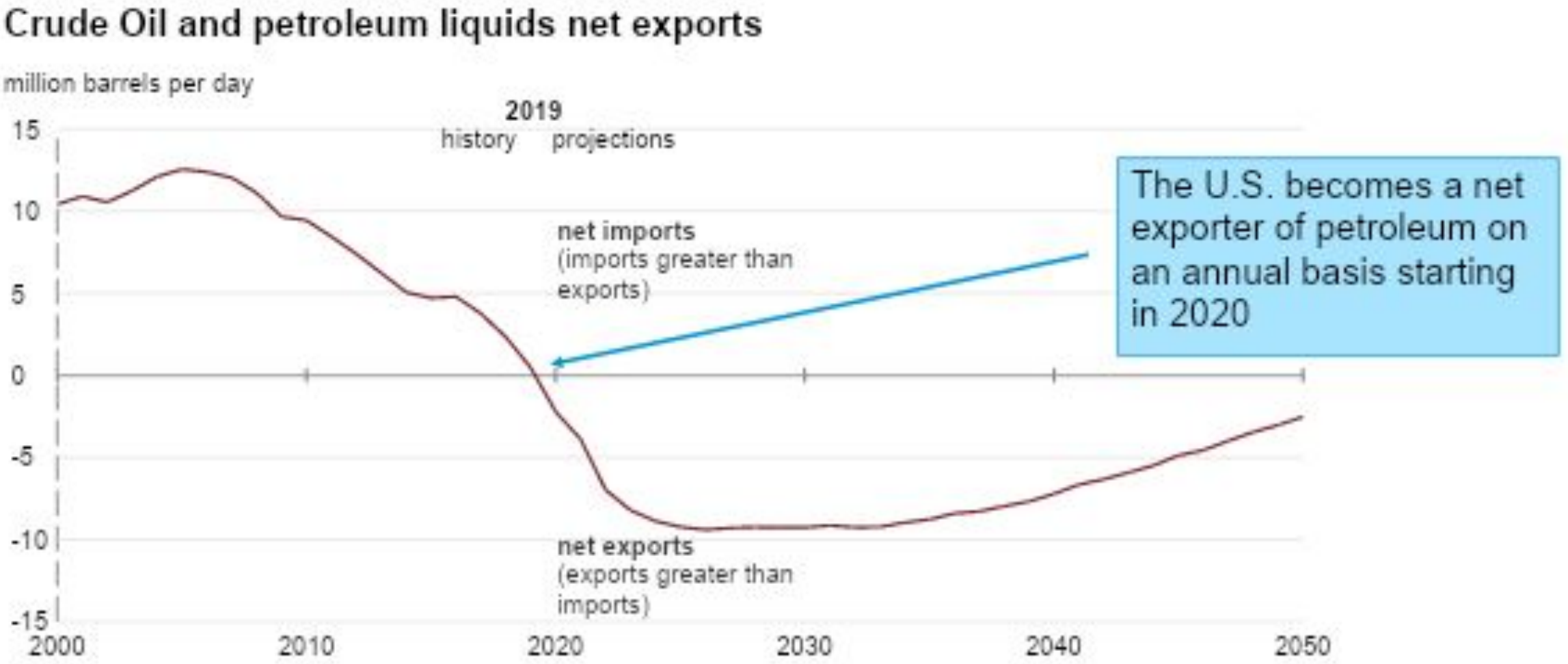


Questions

Appendix

Appendix: Oil Industry Background

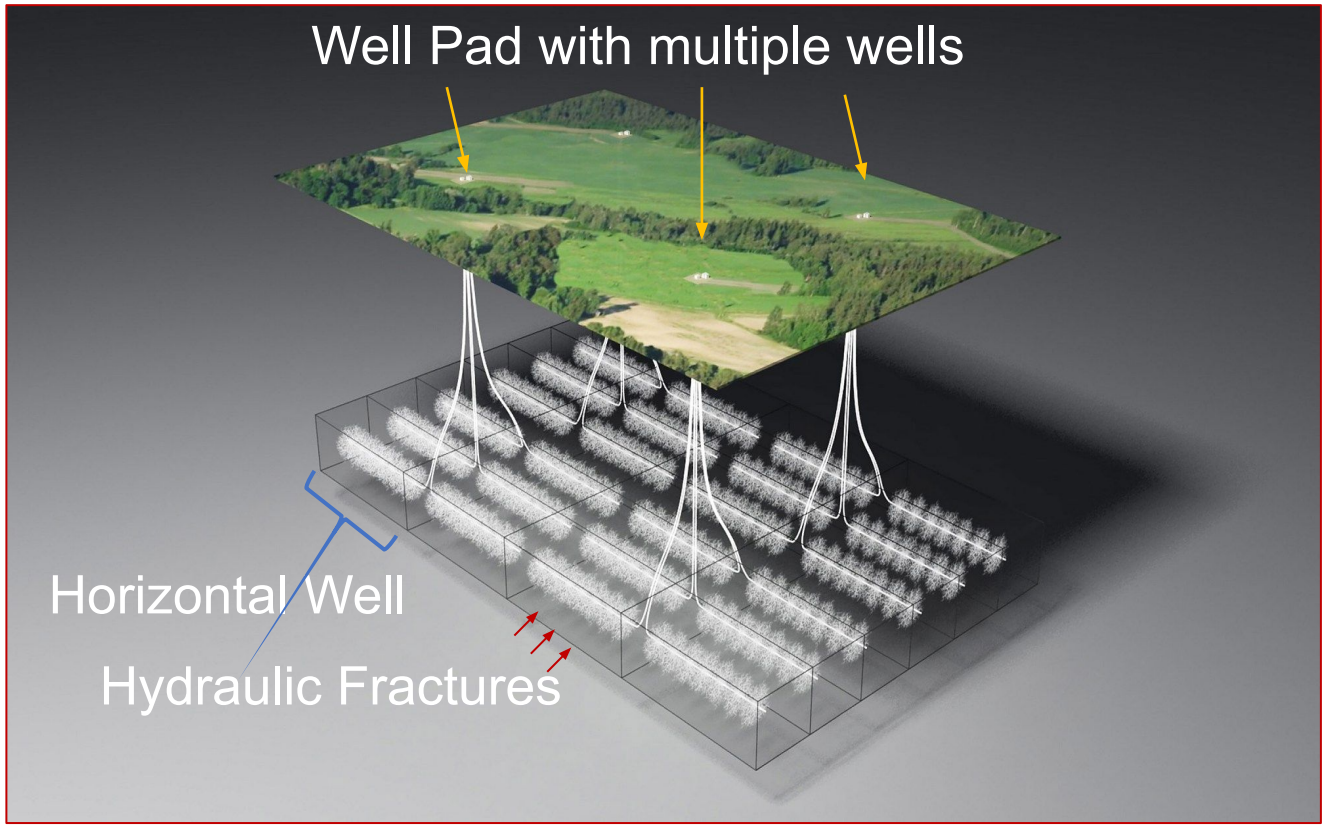
The United States exports more petroleum than it imports from 2020 to 2050



Data Source: U.S. Energy Information Administration, Annual Energy Outlook 2020 (AEO2020) Reference case

Unconventional Reservoirs

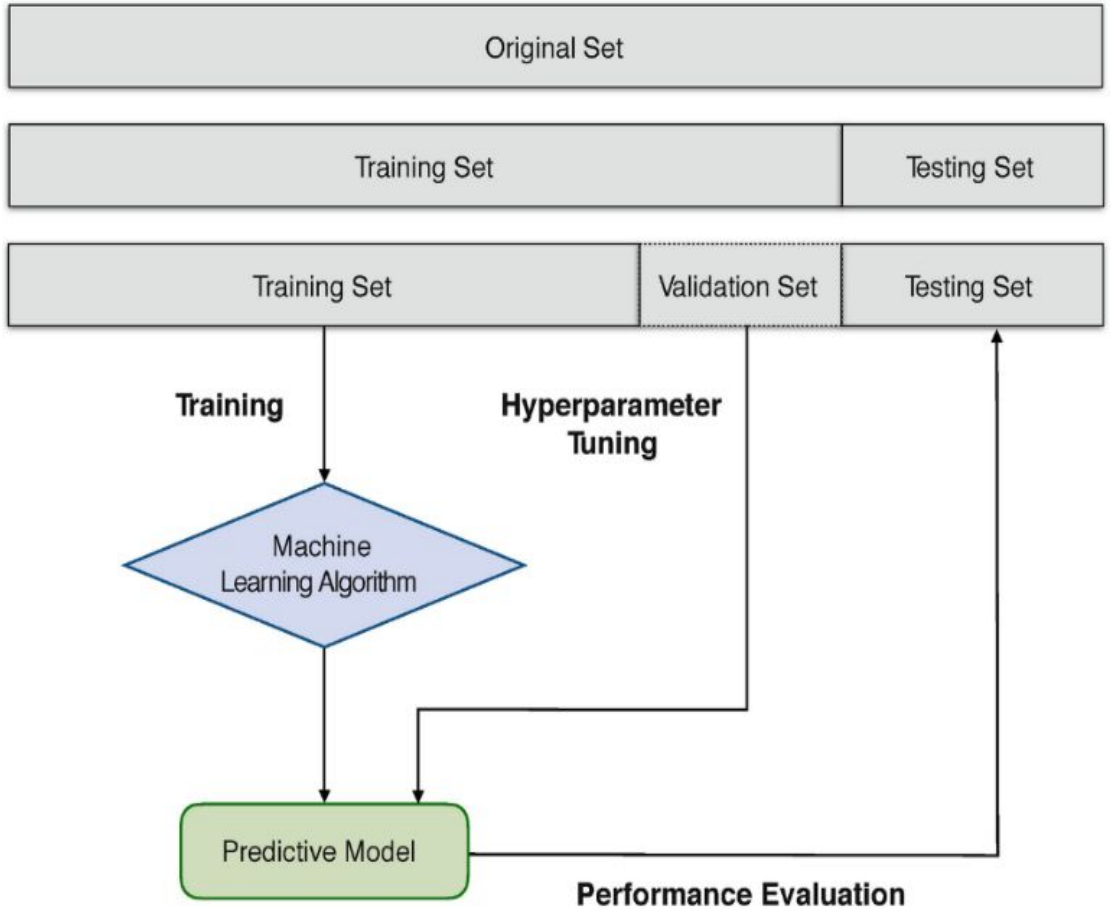
- Very low permeability
- *Horizontal* wells
- *Multistage* fracturing
- Well pad with multiple wells



Appendix: Machine Learning Introduction

Supervised Learning

- Train set
  - ML algorithm “learns” data
- Validation set
  - ML algorithm “sees” data
- Testing set
  - ML algorithm “predicts”



Supervised Learning

- **Purpose:** Optimize a performance measure
  - Inclusion of a class label or “target” during calculations
  - Examples: Regression, Classification

Sample			…		Label
1					
2					
⋮					⋮
m					

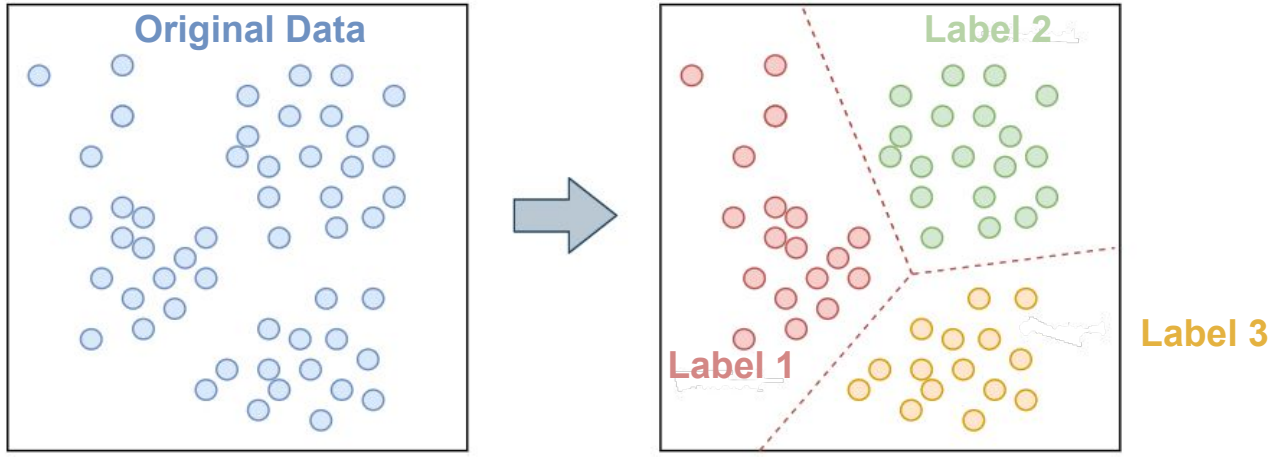
Predicted Label
⋮

Historical/observed oil production represents target variable in this study

Unsupervised Learning

Purpose: discover inherent patterns in the data

- Typically excludes class label or “target” during calculations but not always
- Examples: Clustering and Dimension Reduction



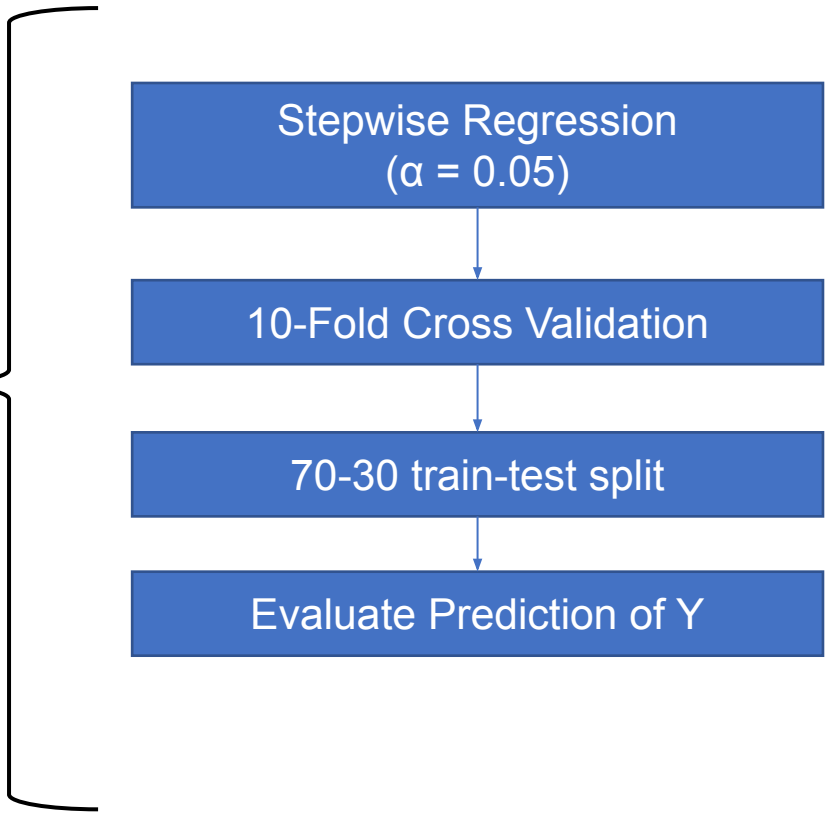
Appendix: Design of Experiments

Research Questions

- **RQ1:** How effective is Arps Model in explaining the variance of the field data used in this study?
- **RQ2**: Is there a statistical relationship between static well variables and cumulative production?
- **RQ3:** How effective is Arps Model in **predicting** the target variable
- **RQ4**: Can Arps Variables act as an effective feature extraction method to predict cumulative oil production?
- **RQ5:** Can PCA as an effective feature extraction method to predict cumulative oil production?
- **RQ6:** Can the combination of Arps variables and PCA be used as an effective feature extraction method to predict cumulative oil production?
- **RQ7:** Does including the well variables aid the prediction performance of the proposed algorithms?
- **RQ8:** Using the same prediction framework as RQ7, does using MLP instead of LR help the prediction accuracy?

RQ2: Feature Selection of Static Well Variables

Inputs	X1	Depth Total Diller
	X2	True Vertical Depth
	X3	Depth Total Projected
	X4	CLL
	X5	Total Proppant
	X6	Proppant per Foot
	X7	Fluid per Foot
	X8	Proppant Fluid Ratio
	X9	Total Fluid
	X10	Status Code
	X11	Oil Gravity
	X12	Sub-Basin
	X13	Bottom Hole Latitude
	X14	Bottom Hole Longitude
	X15	Surface Latitude
	X16	Surface Longitude
	X17	County Name
Output	**Y**	36-month cumulative oil

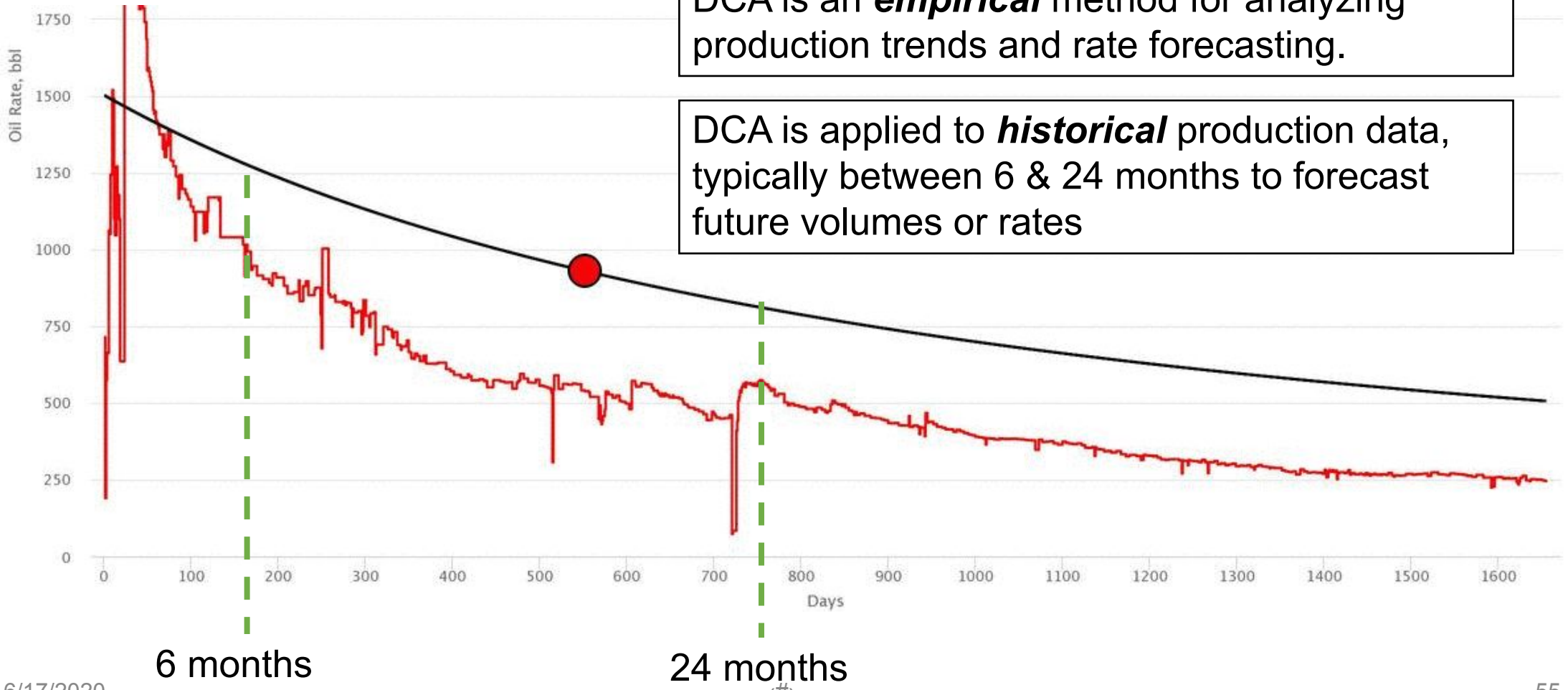


$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{17} X_{17}$$

Decline Curve Analysis (DCA)

DCA is an ***empirical*** method for analyzing production trends and rate forecasting.

DCA is applied to ***historical*** production data, typically between 6 & 24 months to forecast future volumes or rates



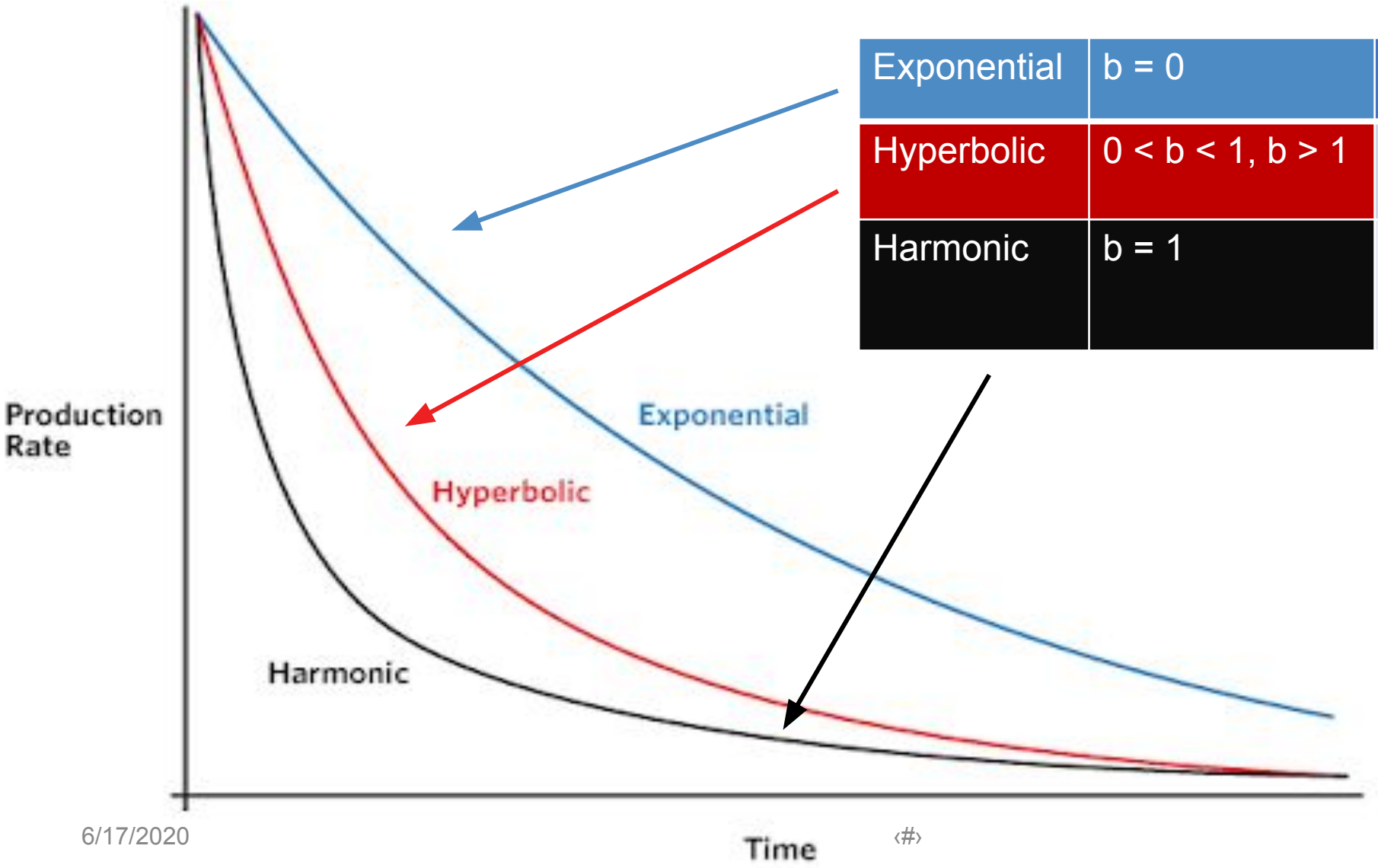
Arps DCA Model

- $$q(t) = \frac{q_i}{(1 + bD_i t)^{1/b}}$$

- $q(t)$ = production rate at time t
- q_i = initial production rate
- D_i = decline constant or “nominal decline rate”
- b = decline exponent or “degree of curvature”

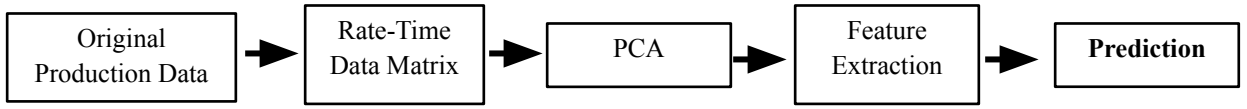
“This natural declining trend is attributed to number of factors including fluid mechanics in porous media, changes in reservoir pressure, changing relative volumes of fluids through, and efficiency of vertical movement by drilling equipment” (Okoro, 2019)

Mathematics of DCA



Exponential	b = 0
Hyperbolic	0 < b < 1, b > 1
Harmonic	b = 1

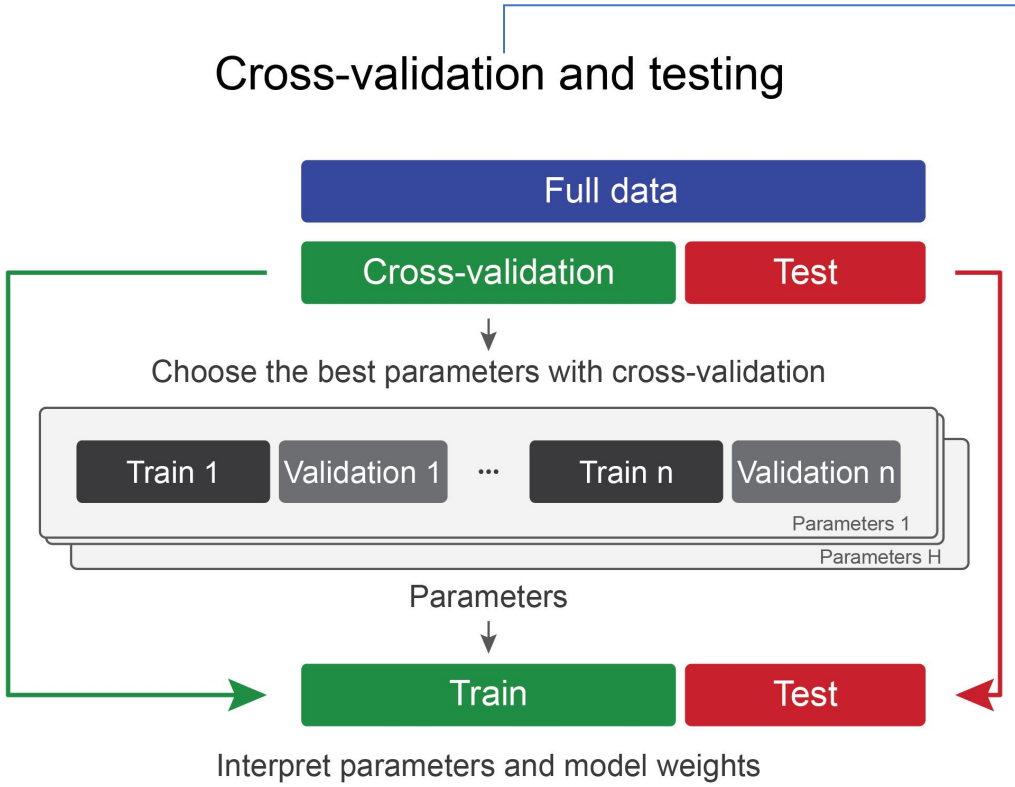
Dataset Transformation for PCA



Well ID	Production Month 1	Production Month 2	…	Production Month *n*
1				
2				
⋮				
448				

Well ID	PC1	PC2	…	PC*n*
1				
2				
⋮				
448				

Cross-validation: creating *reproducibility* in experiments

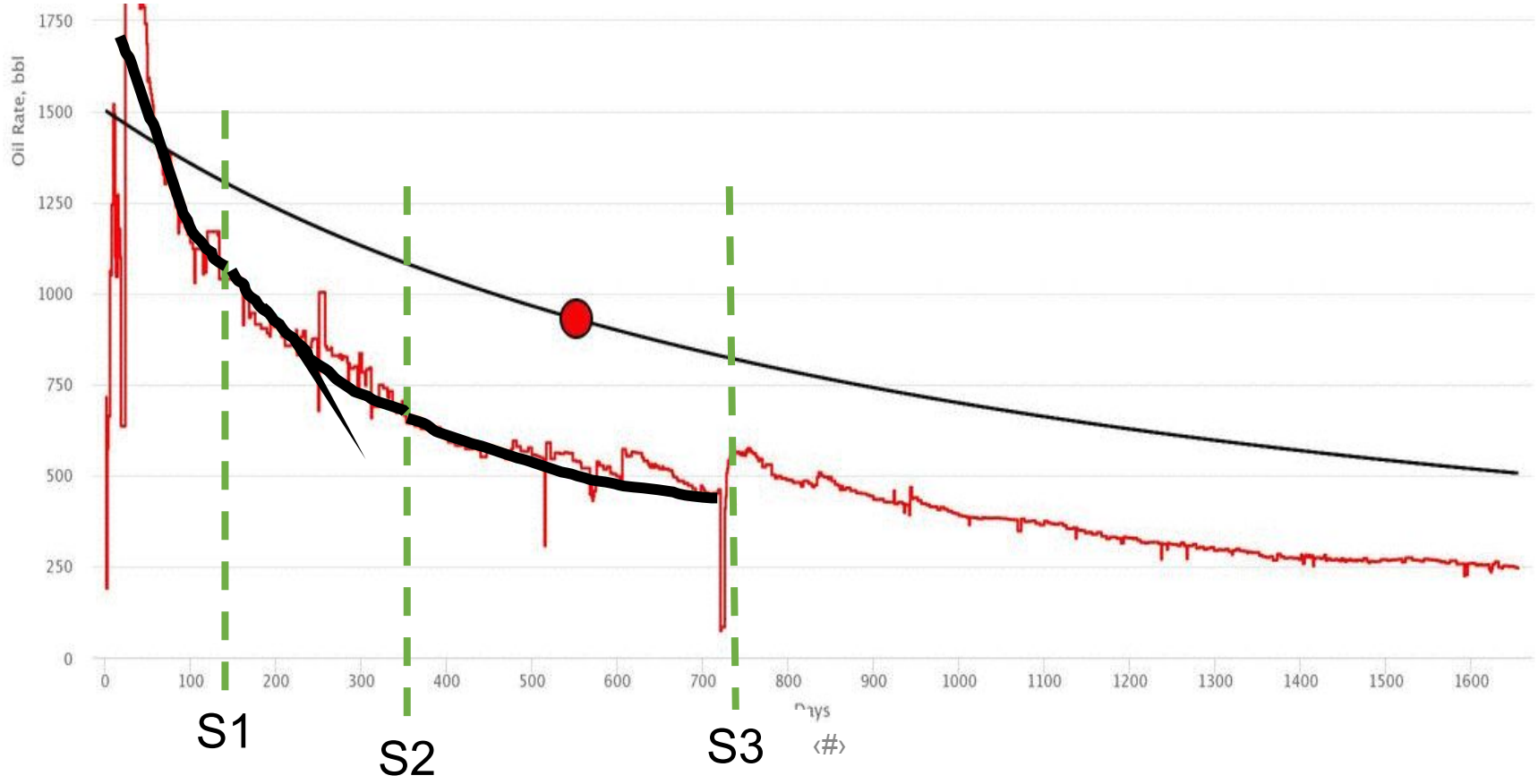


K-Fold Cross Validation Data Partition

K = 1	Holdout	Train	Train	Train	Train
K = 2	Train	Holdout	Train	Train	Train
K = 3	Train	Train	Holdout	Train	Train
K = 4	Train	Train	Train	Holdout	Train
K = 5	Train	Train	Train	Train	Holdout

Evaluating Arps Model on Field Data

Fit Arps Model to each scenario of data → Evaluate Goodness-of-Fit → Assess as Feature Extraction



Design of Experiments: RQ7

- Including extracted features with well parameters

RQ2 Results

Significant Well Features

Extracted time-series features

(1) Arps
(2) PCA
(3) Hybrid

Stepwise Regression
(α = 0.05)

10-Fold Cross Validation

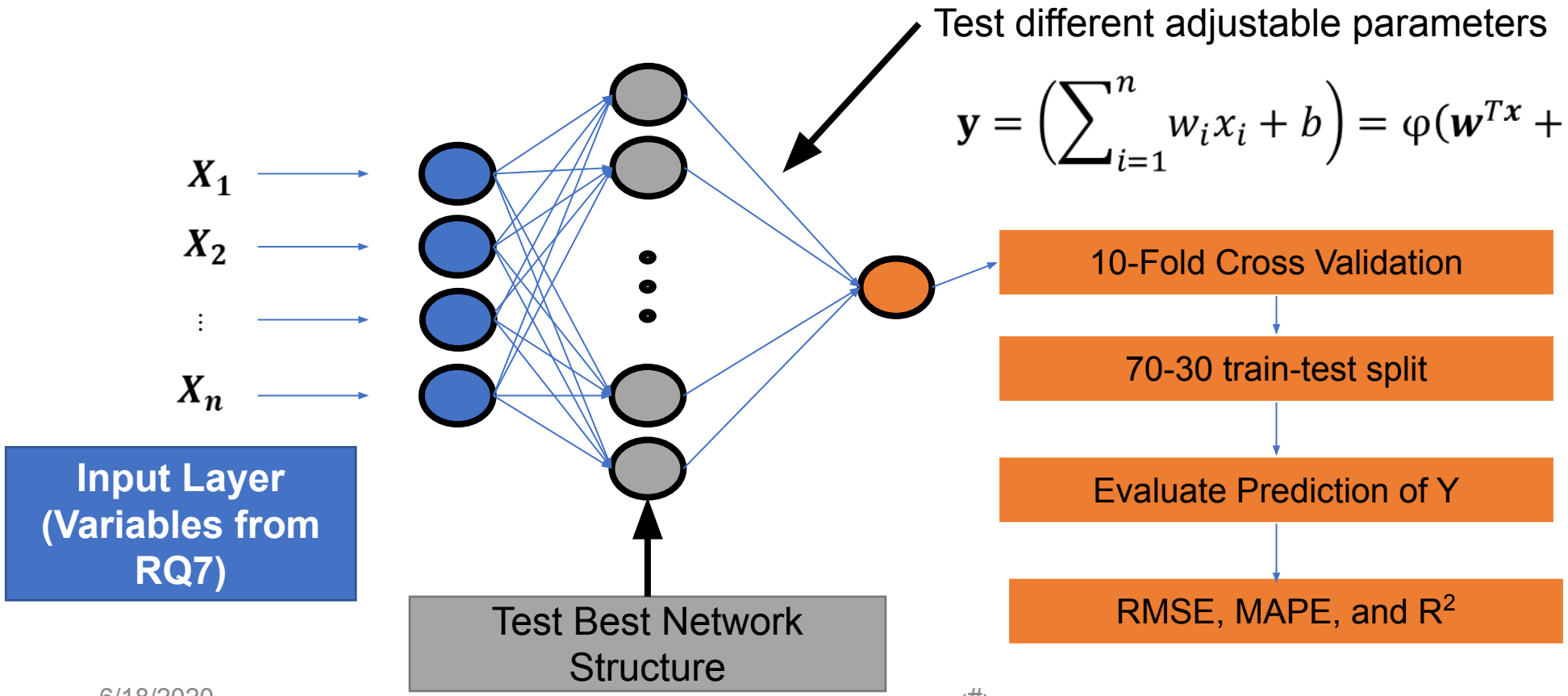
70-30 train-test split

Evaluate Prediction of Y

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Design of Experiment: RQ8

Adding model complexity through MLP using existing input variables as RQ7:



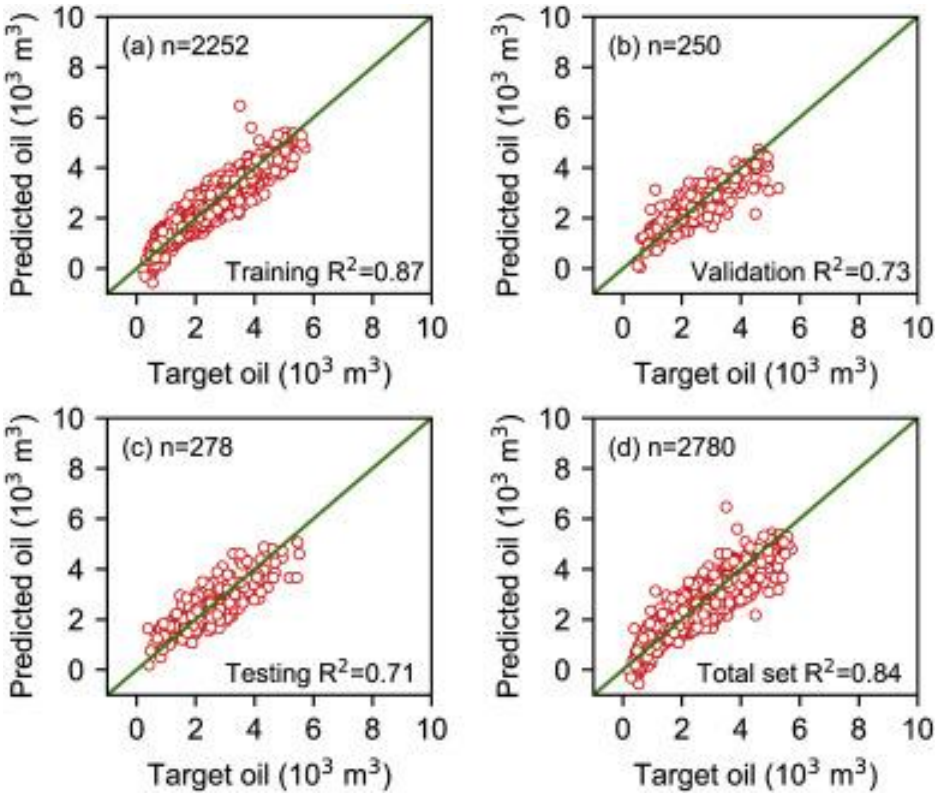
Appendix: Literature Review

Summary of Key Related Works

Source	Study Purpose	Methods	Evaluation Metrics	Outcomes	Relation to this study
[1], [2], [3]	Compare machine learning time-series predictions to empirical DCA methods	LSTM ANN	R^2, MAPE, RMSE, MSE	Successful time-series application in predicting oil and gas production in short-term intervals	Comparison to DCA
[4]	Evaluate static parameters to reconstruct dynamic profiles	PCA, MLP	R^2, MAPE, RMSE	Applied PCA to static well parameters as inputs to MLP to predict DCA model coefficients	Incorporate DCA parameters for model building
[5]	Prediction of initial flow rates and evaluate variable importance	MLP	MSE, R^2	Used pressure and time well log data to predict initial oil flow rates to 93% R^2	Study of initial flow rates (Qi in Arps Model)
[6], [7]. [8]	Prediction of cumulative oil production and evaluate variable importance of static well parameters	LR, MLP	R^2, MAPE, RMSE, MSE	Predicted cumulative oil production with resulting test set R^2 71% (6-month) and 72% (18-month)	Incorporates static well parameters including completions, geology, location, PVT data
[9]	Prediction of cumulative oil production and evaluate variable importance of static well parameters specific to EFS	LR and MLP	R^2, MAPE, RMSE	Predicted 6-month cumulative oil production with resulting test set R^2 39% (LR) and 62% (MLP)	EFS
[10]	Study efficacy of FPCA on oil production time-series	LR and PCA	R^2, MAPE, RMSE	Reconstruct production profiles to less than 5% MAPE using first 4 PCs	Feature Extraction using PCA
[11], [12]	Apply FPCA to match historical production and predict future values	PCA, LR	R^2, MAPE, RMSE	MAPE: 21.87% to match field data [11] MAPE: 10.3% to match simulated forecasts [12]	Feature Extraction using PCA for prediction

Appendix: Literature Review

- Shuhua Wang, Zan Chen, Shengnan Chen,
- Applicability of deep neural networks on production forecasting in Bakken shale reservoirs,



Variables	Parameters	Range	Mean	Standard deviation
Independent	Easting (10_5 m)	5.71–6.77	6.42	0.16
	Northing (10_6 m)	5.45–5.55	5.5	0.01
	True vertical depth (m)	728.90–2338.50	1545.3	93.34
	Well lateral length (m)	186.00–3040.60	1254.7	282.95
	Upper Bakken thickness (m)	1.13–6.82	2.84	0.84
	Middle Bakken thickness (m)	1.13–15.11	10.05	2.21
	Lower Bakken thickness (m)	2.56–11.19	5.93	1.29
	Number of fracture stages	1–50	15	8
	Fracture spacing (m)	17.44–716.56	117.88	68.68
	Average fluid pumped per stage (m_3)	0.20–221.00	33.6	21.25
	Load fluid recovery factor (%)	0.00–90.00	18.41	19.26
	Average proppant per stage (tons)	2.00–99.00	6.69	4.27
Dependent	6 months oil production (10_3 m_3)	0.01–8.22	2.51	1.45
	18 months oil production (10_3 m_3)	0.05–17.96	5.35	3.19

(Grujic, Da Silva, & Caers, 2015)

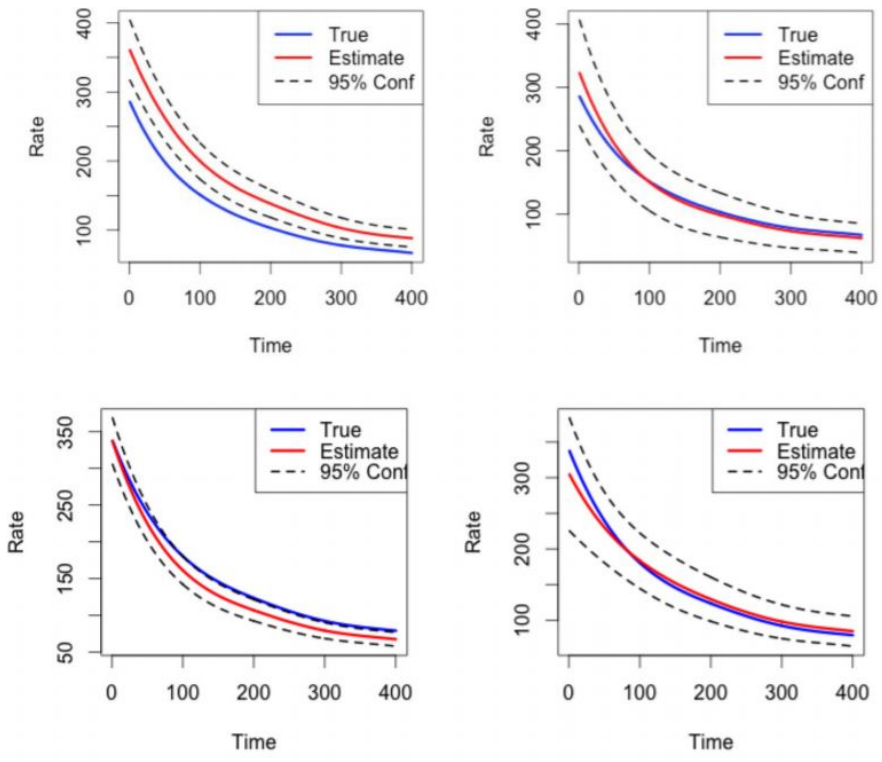


Table 1—Summary of all available data

	Type	Parameter	Unit	Source	Kind	Abbreviation
OUTPUT	Production	Oil Rates	stb/day	raw	function	-
		Gas Rates	stb/day	raw	function	-
		Water Rates	stb/day	raw	function	-
INPUT	Completions	Number of Completion Stages	#	raw	scalar	CMP STAGES STIMULATED
		Total Amount of Injected Fluid	gal	raw	scalar	CMP TOTAL FLUID PUMPED GAL
		Total Amount of Injected Proppant	lbs	raw	scalar	CMP TOTAL PROPPANT USED
		Stimulated Lateral Length	ft	raw	scalar	CMP STIMULATED LATERAL LENGTH
		Total Amount of Slick Water	bbl	raw	scalar	CMP AMT SLICKWATER BBL
		Total Amount of Injected x-link fluid	bbl	raw	scalar	CMP AMT CROSSLINK BBL
		Completion Stage Interval	ft	raw	scalar	CompStageInterval
		Total amount of linear fluid	bbl	raw	scalar	CMP AMT LINEAR BBL
	Geographical	X location	ft	raw	scalar	GeolX Rel
		Y location	ft	raw	scalar	GeolY Rel
		Z location (depth)	ft	raw	scalar	GeolZ
	PVT	Oil API Gravity	api units	raw	scalar	GeolAPIGrav
	Petrophysical	Total organic content (TOC)	%	well log - interpretation	scalar	PetroTOC
		Clay Content	%	well log - interpretation	scalar	PetroVClay
		Water Saturation	%	well log - interpretation	scalar	PetroSwt
		Porosity	%	well log - interpretation	scalar	PetroPor
		Total Amount of Quartz	%	well log - interpretation	scalar	PetroVQtz
		Amount of Pyrite	%	well log - interpretation	scalar	PetroPyr

Method	Average MAPE	% Data within 95% CB
OLS Regression	21.87%	47%

Appendix: Results Tables

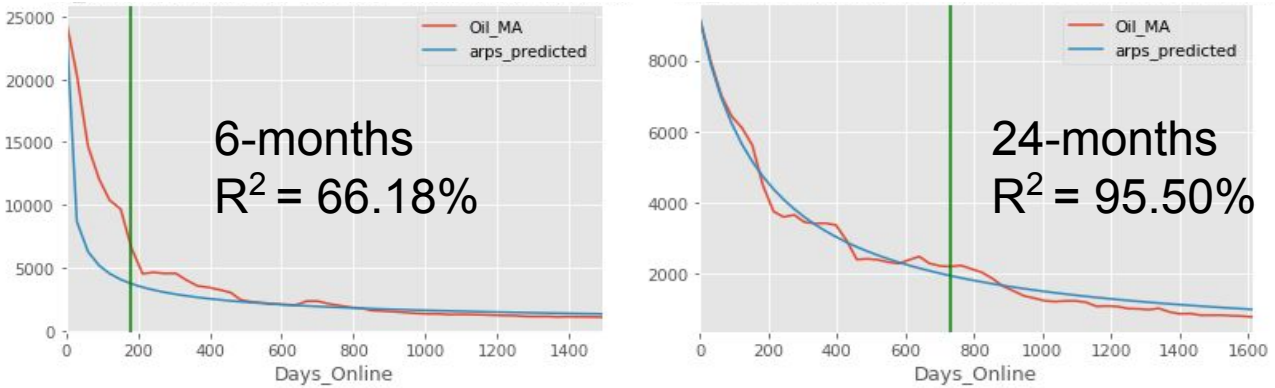
RQ1 Results: Evaluating Arps Model vs PCA on Field Data

Goodness-of-fit metrics using Arps Model

Scenario	RMSE	MAPE	R^2
6 Months	14253	16.26%	66.18%
12 Months	4989	8.53%	91.63%
24 Months	3659	6.31%	95.50%

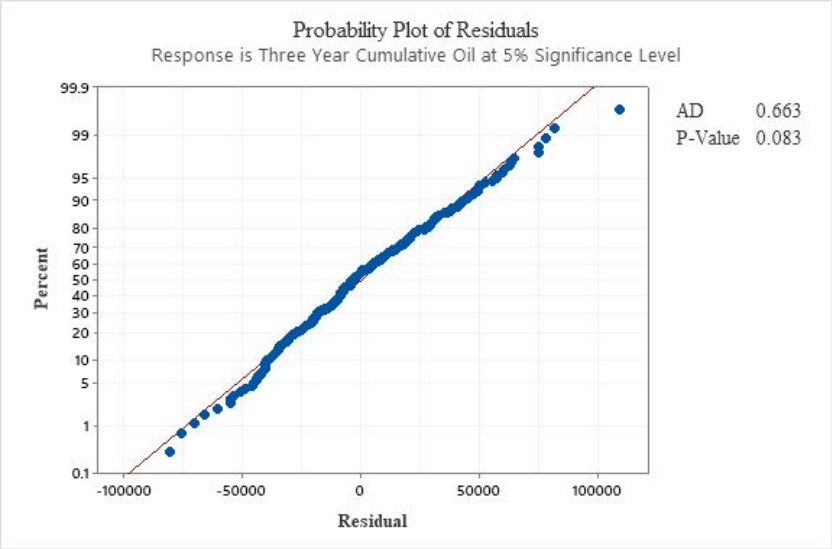
Cumulative Proportion of Variance captured by PCA

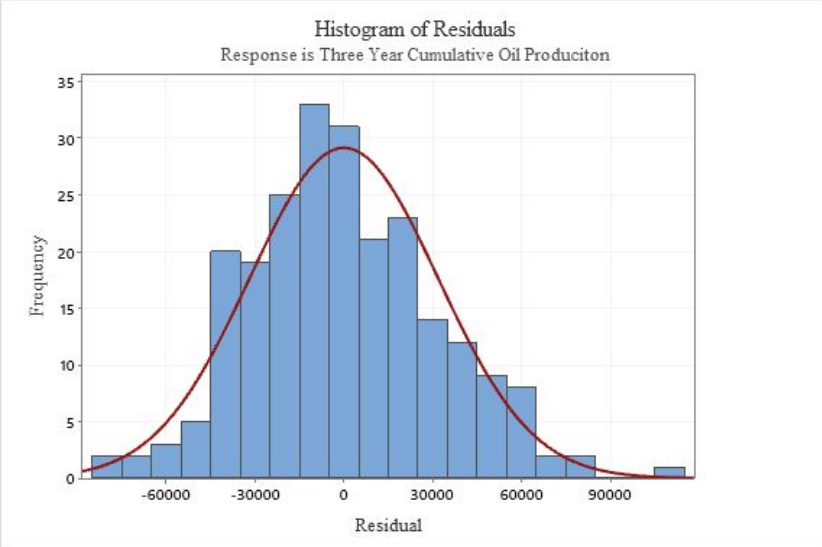
Scenario	PC1	PC2	PC3
6-months	89.6%	98.5%	99.7%
12-months	90.6%	97.7%	99.5%
24-months	89.1%	97.1%	99.4%

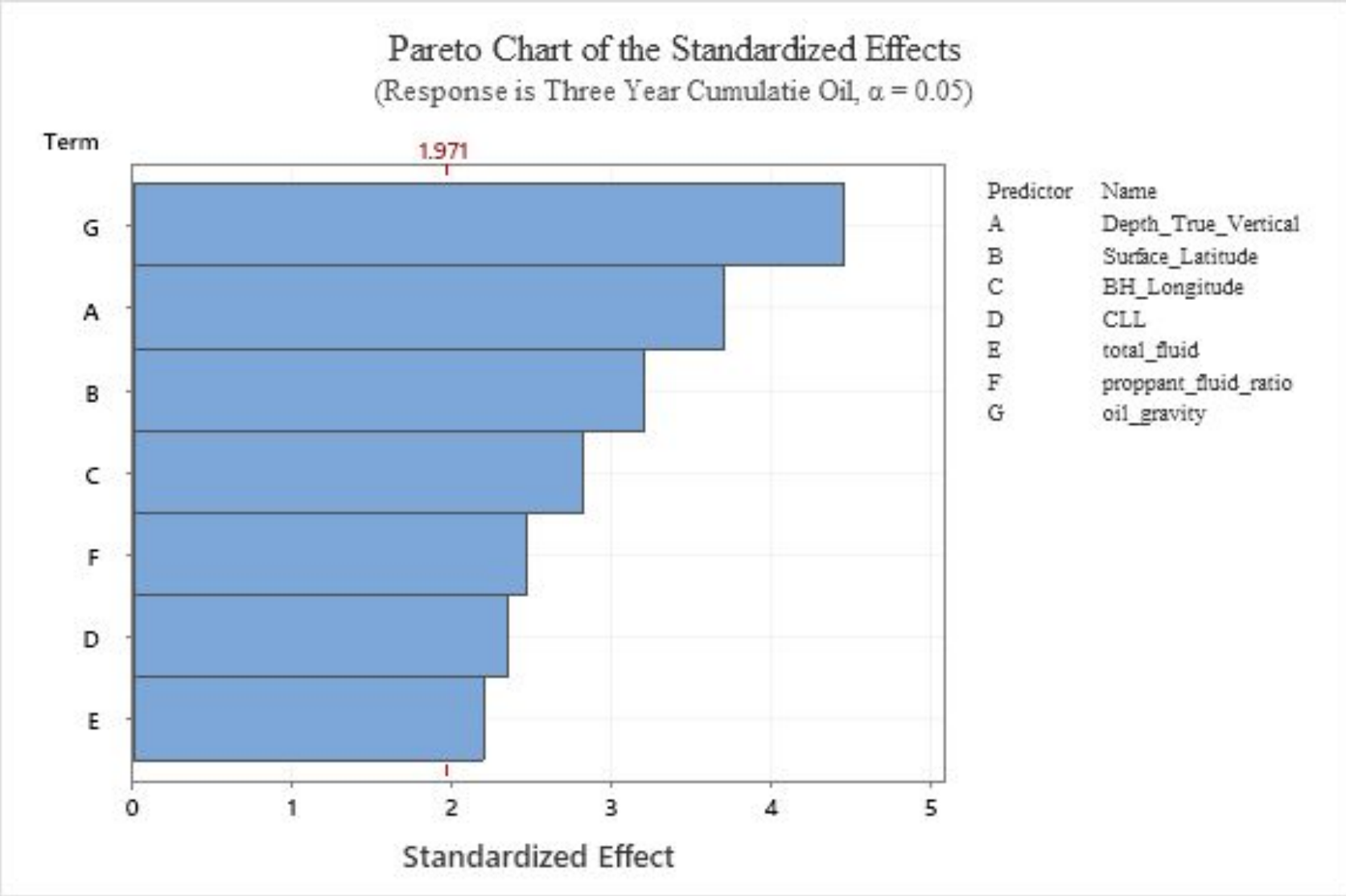


Example Arps Model curve-fits

Results RQ2

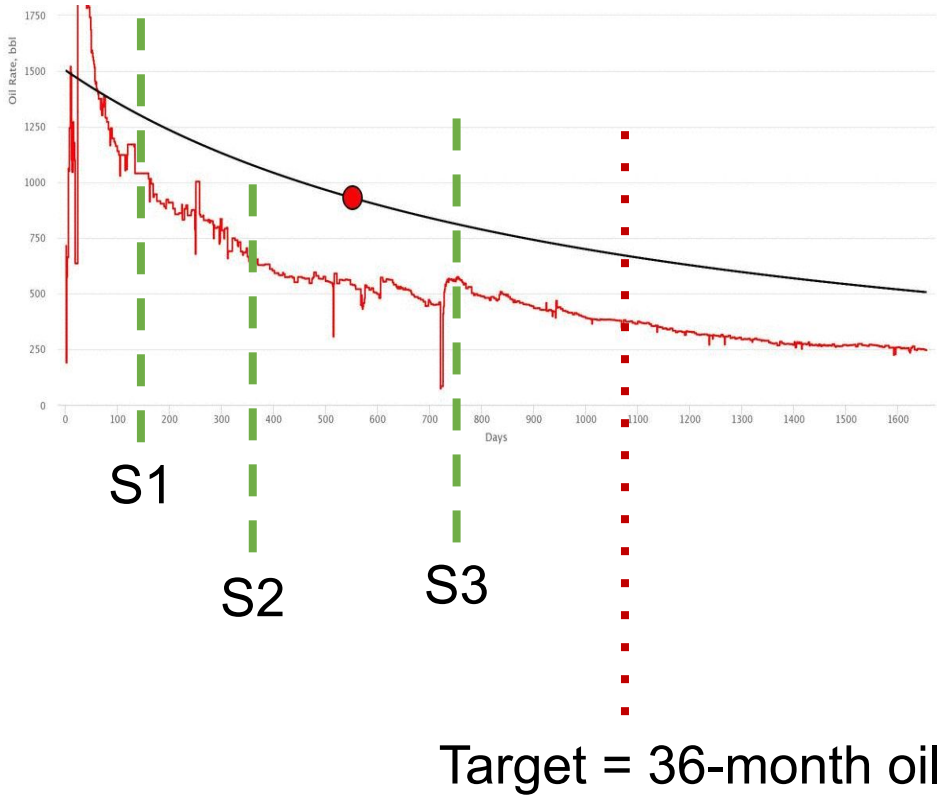

Probability Plot of Residuals
Response is Three Year Cumulative Oil at 5% Significance Level
AD 0.663
P-Value 0.083
Percent
Residual


Histogram of Residuals
Response is Three Year Cumulative Oil Produciton
Frequency
Residual


Pareto Chart of the Standardized Effects
(Response is Three Year Cumulatie Oil, α = 0.05)
Term
1.971
G
A
B
C
F
D
E
Standardized Effect
Predictor Name
A Depth_True_Vertical
B Surface_Latitude
C BH_Longitude
D CLL
E total_fluid
F proppant_fluid_ratio
G oil_gravity

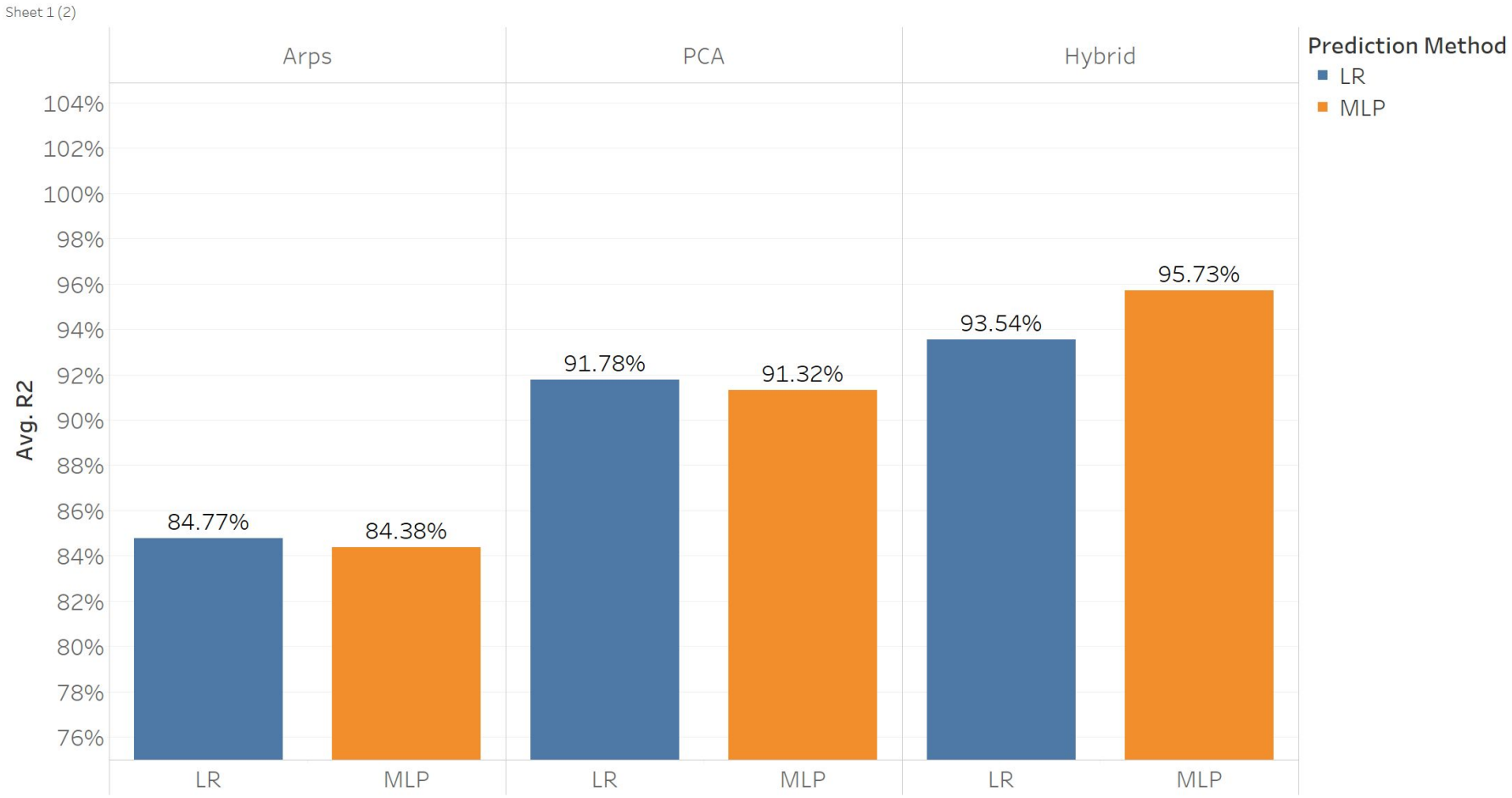
RQ3 Results

Fit Arps Model to each scenario of data → Predict target variable → Assess Prediction quality



Scenario	RMSE	MAPE	R^2
S1: 6 Months	26084	28.3%	44.16%
S2: 12 Months	17130	16.23%	77.41%%
S3: 24 Months	13263	8.81%	86.46%

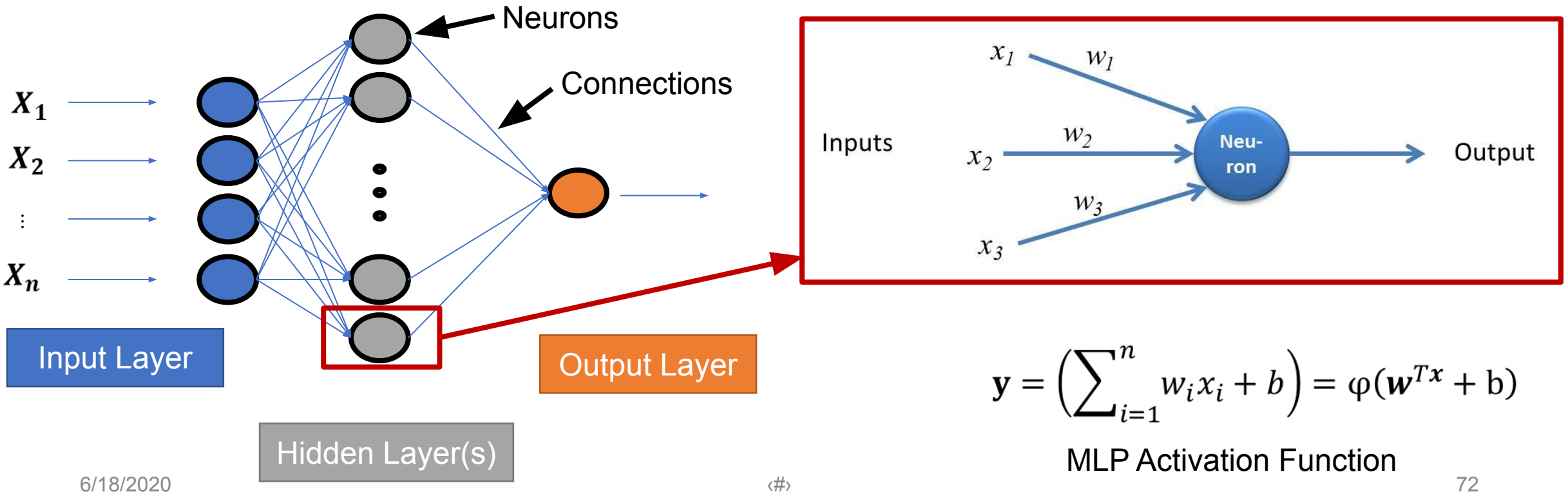
Appendix: RQ8 LR vs MLP by Feature Extraction



Average of R2 for each Prediction Method broken down by Feature Extraction. Color shows details about Prediction Method. The marks are labeled by average of R2.

Artificial Neural Networks (ANN)

- Experimental branch of science to simulate human learning
  - Multilayer Perception (MLP) most famous and widely used ANN
  - Nonlinear approach to production forecasting

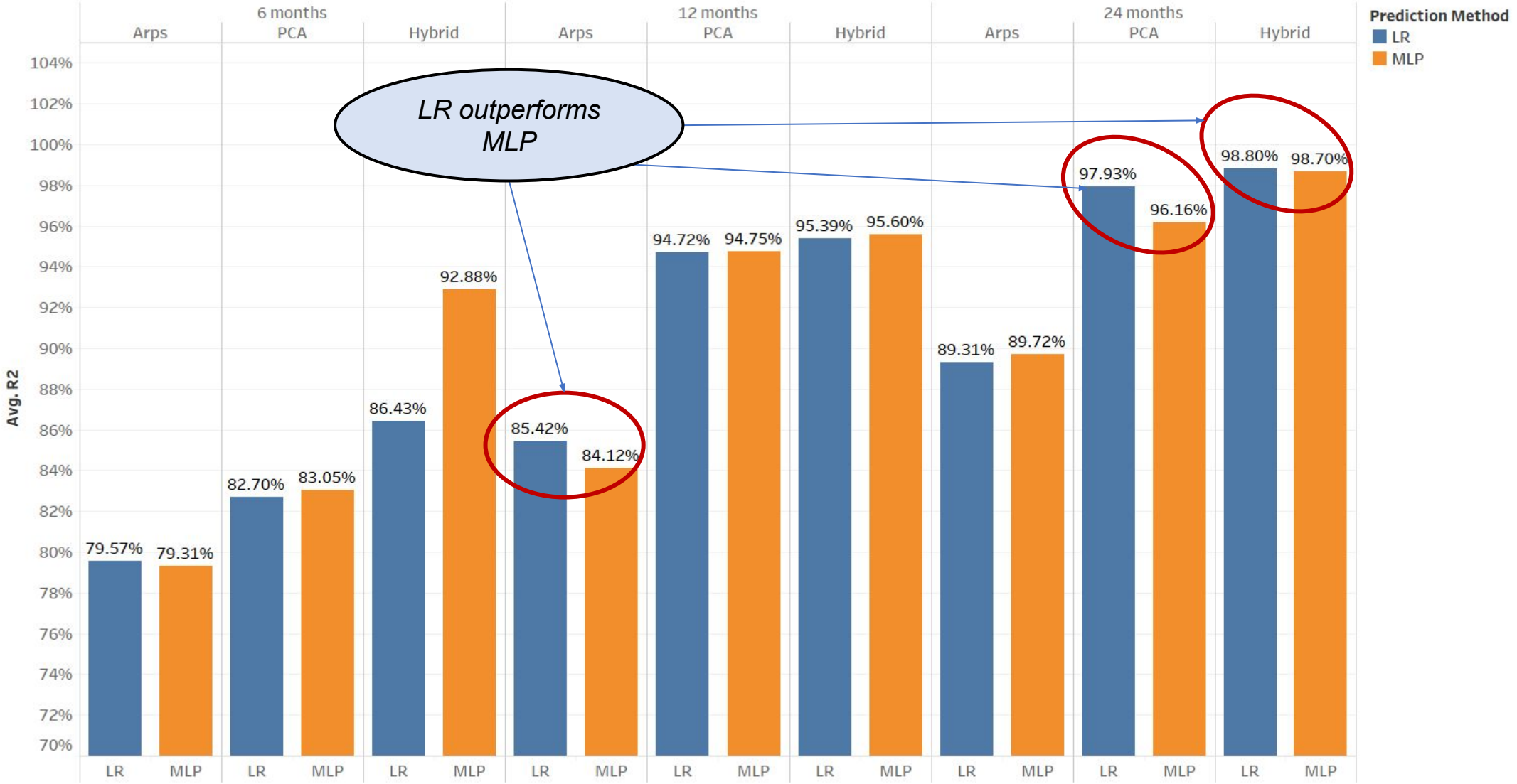


$$\mathbf{y} = \left(\sum_{i=1}^{n} w_i x_i + b\right) = \varphi(\boldsymbol{w}^{T}\boldsymbol{x} + \mathrm{b})$$

MLP Activation Function

RQ8 Results: Broken down by feature extraction and Scenario

A closer look at answering research question RQ8



LR Limitations

- Linear Regression limitations•
  - **Only Linear:**
    - Only capable of fitting the data to linear models.
    - – Non-linear modes might be able to explain and predict better.
  - •**Sensitive to outliers:–**
    - The estimation of β0will be skewed significantly to account for a handful of outliers.
  - •**Heavy design necessary**: The prediction performance heavily relies on the design of the regression model.
    - – Inclusion and exclusion of an attribute has significant impact on prediction performance.
  - •**Limited prediction power:** The method is not designed for prediction.