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Adapting Shallow and Deep Learning Algorithms to Examine Production Performance – Data Analytics and Forecasting

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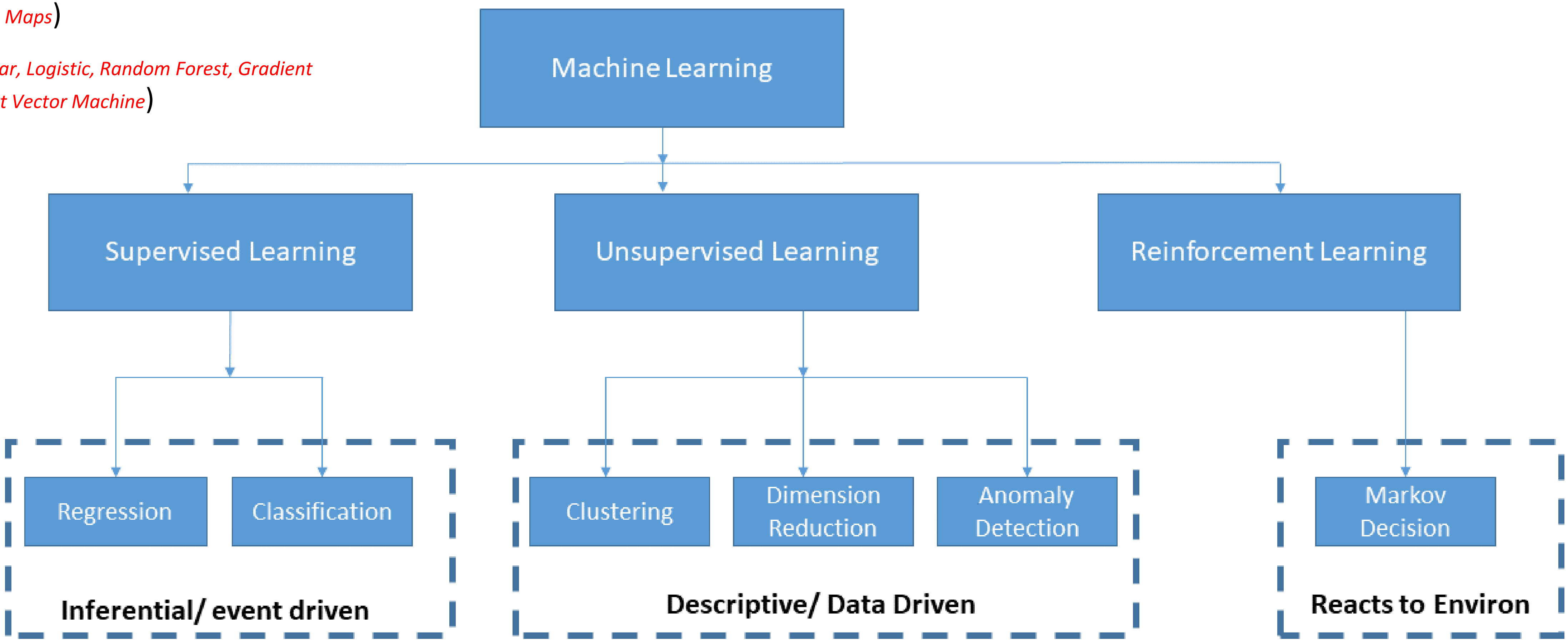
OUTLINE

- Shallow Learning – A Closer Look
- Deep Leaning – Nuts and Bolts
- Case Study I – Production Performance in Delaware Basin
- Case Study II – Decline Curve HM and Forecast

Methods of Shallow Learning

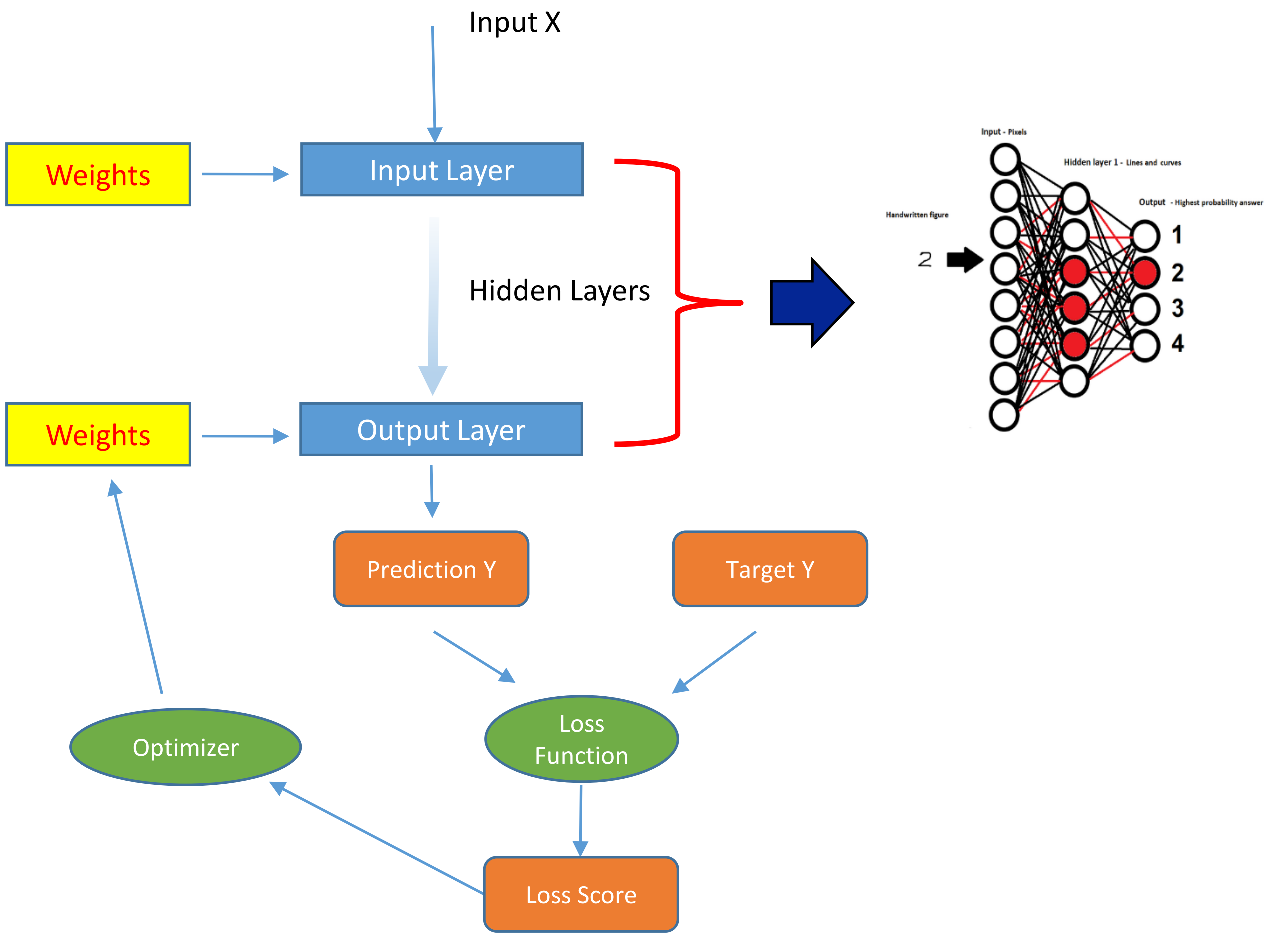
Classification (*e.g. Decision Tress, Neural network. K-means clustering, Self-Organizing Maps*)

Regression (*e.g. Linear, Logistic, Random Forest, Gradient Boosting Machine, Support Vector Machine*)



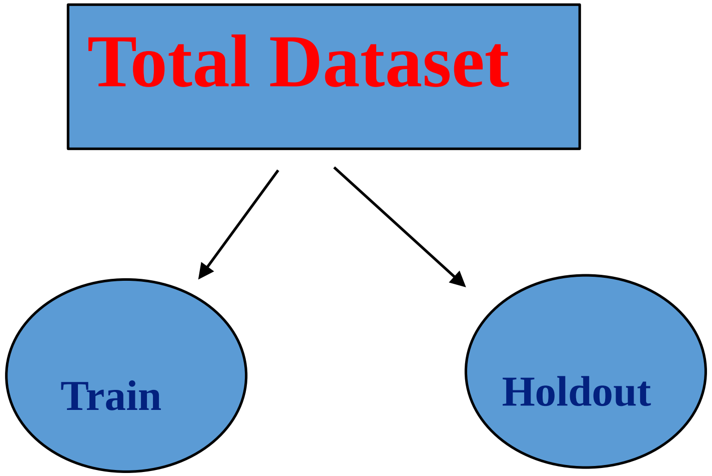
Deep Learning Architecture

- ✓ **Input layer** – data is fed in
- ✓ **Output layer** – prediction
- ✓ **Hidden layers** – neurons interconnected
- ✓ **Red neurons** – amplify the values which activates the neuron it is feeding to by altering weights and biases
- ✓ This handover and gradual elimination process **piece meals information** for final task, e.g. image recognition
- ✓ Different layers build rough **hierarchy of different features**
- ✓ With each pass a loss function guides the optimizer **to alter the magnitude and direction of weight change** for the following pass
- ✓ All layers are **updated simultaneously**



Machine Learning Moving Parts

- ✓ Problem Description – Identifying features and targets
- ✓ Data Cleaning
- ✓ Feature Engineering (domain knowledge)
- ✓ Exploratory Data Analysis
- ✓ Model Selection
- ✓ Model Validation (*k-fold, batches*)
- ✓ Parameter Tuning – Hyper Parameter Search
- ✓ Improving Predictive Capability
- ✓ Saving trained model and application on new datasets



Case Study I

Predicting Production Performance using Reservoir, Completion, Geology, Fluid Data - Wolfcamp Dataset

Dataset Description

5716 horizontal wells
131 predictors

Target – EUR BOE

21 completion
9 reservoir fluid
53 production
26 reservoir
22 well architecture

Completion Variables (21)	
fracVendorName	range
jobStartDate	recompletionFlag
jobEndDate	refracFlag
materialSourceColumn	simulFrac
proppantConcentrationLbsPerBbl	spudDate
proppantLbsPerFoot	stages
producingMethod	totalAdditive
proppantMeshSize	totalAdditiveUOM
proppantType	totalProppantLbs
pumpType	treatmentType
quarterQuarter	

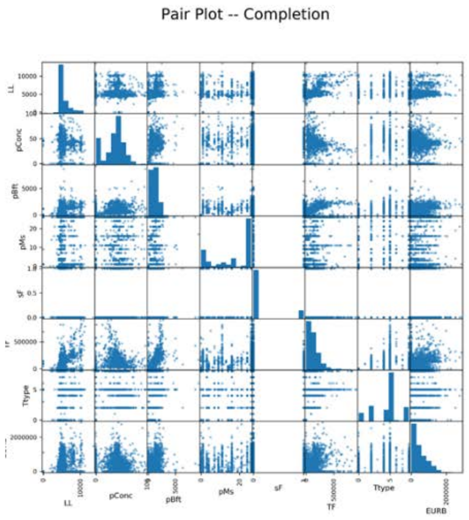
Fluid Vars (9)
gasGravity
grade
gradeGas
gradeOil
oilGravity
primaryProduct
testDryGasGravity
testOilGravity
totalFluidBbls

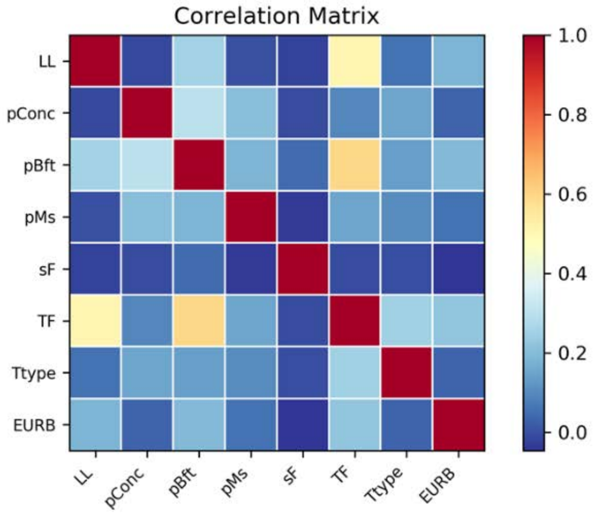
Production Vars (53)	
cum3MonthsBoe	firstGasOilRatio
cum3MonthsGas	firstProductionDate
cum3MonthsOil	lastGasOilRatio
cum3MonthsWater	lastProductionDate
cum6MonthsBoe	lastProductionGas
cum6MonthsGas	lastProductionOil
cum6MonthsOil	lastProductionWater
cum6MonthsWater	maxIpBoe
cum12MonthsBoe	maxIpGas
cum12MonthsGas	maxIpGasPending
cum12MonthsOil	maxIpOil
cum12MonthsWater	maxIpOilPending
cum24MonthsBoe	pracIPGasOilRatio
cum24MonthsGas	twentyFourHourBoe
cum24MonthsOil	twentyFourHourGas
cum24MonthsWater	twentyFourHourGasOilRatio
cum60MonthsBoe	twentyFourHourOil
cum60MonthsGas	twentyFourHourWater
cum60MonthsOil	twentyFourHourWaterOilRatio
cum60MonthsWater	peakProdDate
cumTotalGas	peak3monCumulativeGas
cumTotalOil	peak3monCumulativeOil
cumTotalWater	peak6monCumulativeGas
cumulativeGasOilRatio	peak6monCumulativeOil
EURGas	peak12monCumulativeGas
EUROil	peak12monCumulativeOil
first3MonthsGasOilRatio	

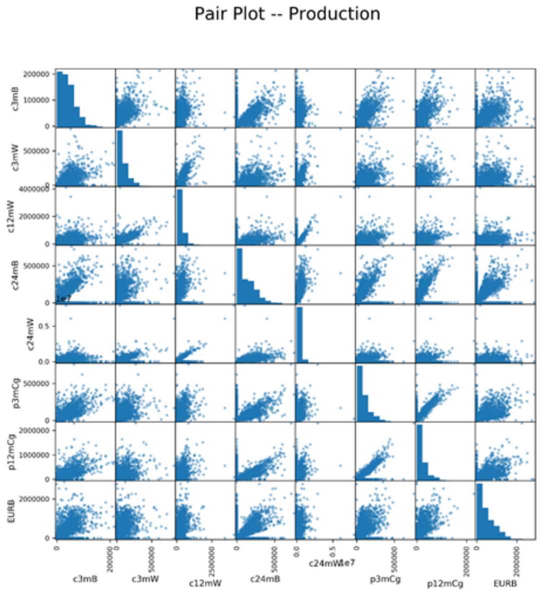
Well Vars (22)	
api10	lowerPerforation
azimuth	numberOfCompletions
casingPressure	perfInterval
chokeSize	perfIntervalSource
completionDate	surfaceCasingDepth
flowingTubePressure	tubingSize
hpdiEntityId	upperPerforation
intermediateCasing	wellbore
lateralLength	wellName
latitude27	wellNumber
linerSize	wellType

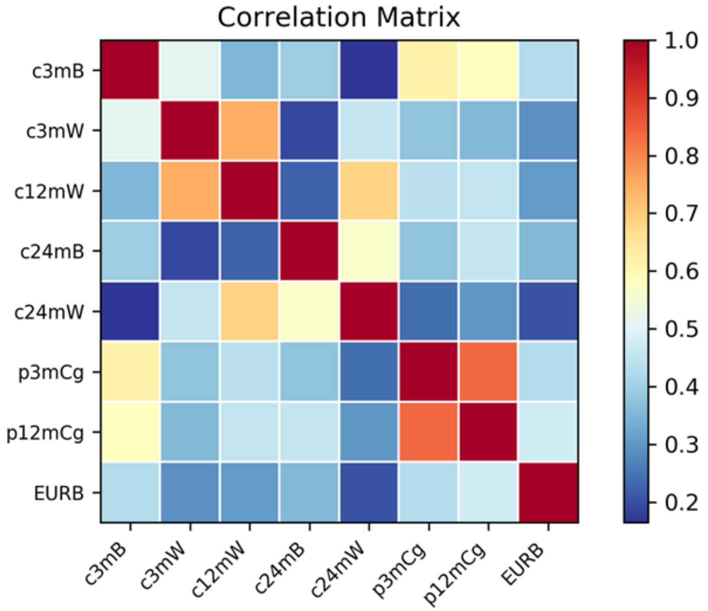
Reservoir Vars (36)	
abstract	padDrill
allocFlag	play
basin	playArea
bottomHoleTemp	reservoir
bottomHoleTempDepth	reservoirAlias
county	section
field	state
geologyZone	survey
leaseName	testFormation
longitude27	totalDepth
nearNeighborFt	township
operator	tvd
outlierFlag	tvdSource

Correlation

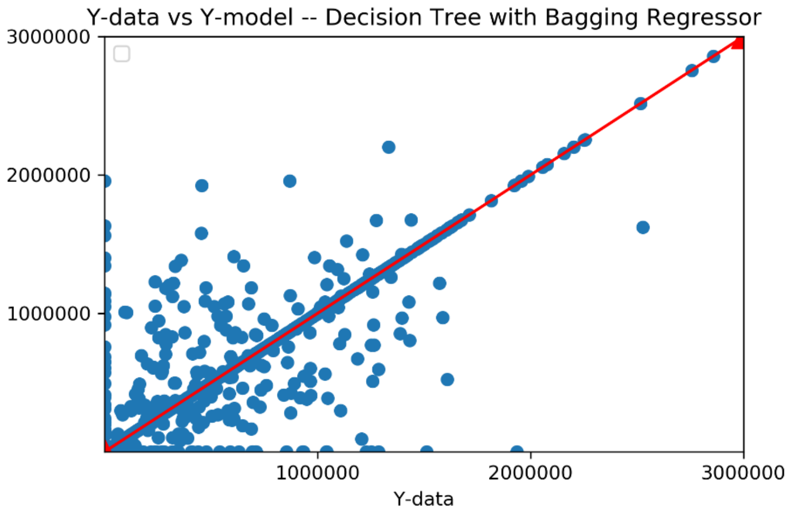




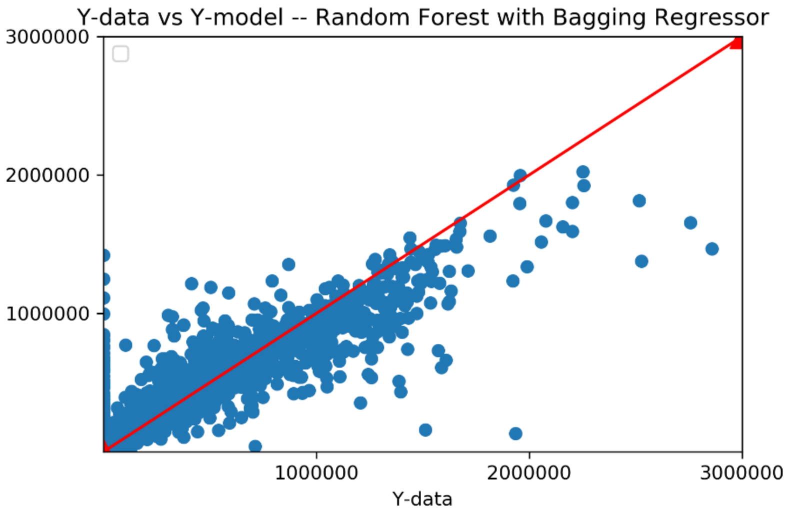




Shallow Learning Results – DT vs RF

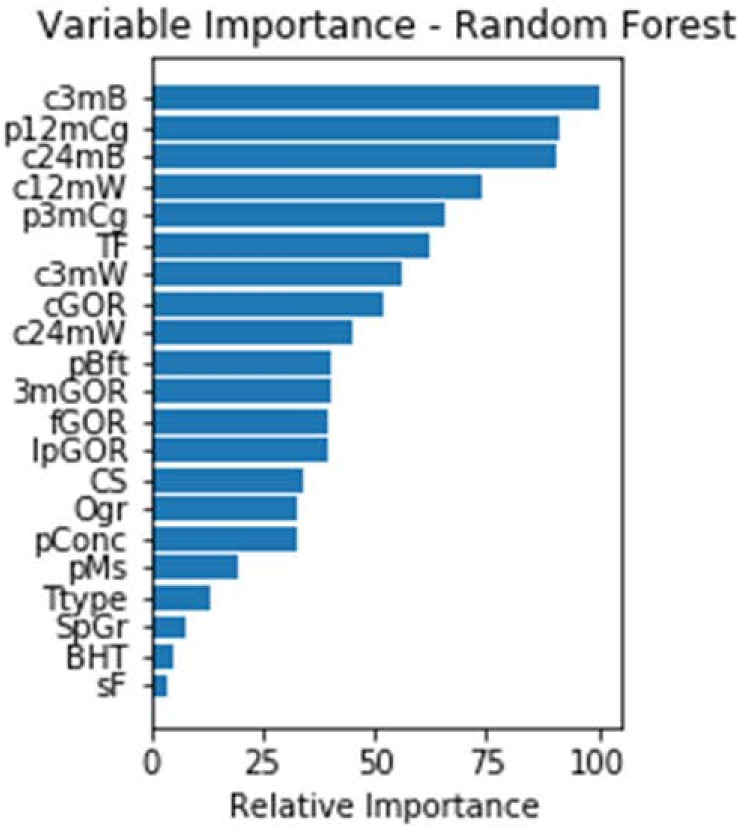


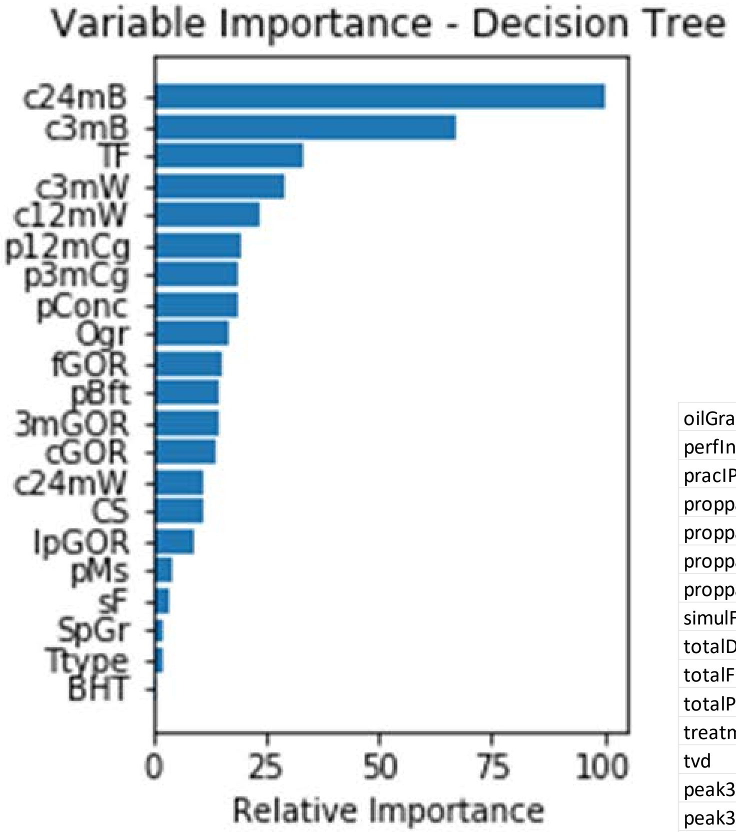
Decision Tree -- Bagging



Random Forrest -- Bagging

Shallow Learning Results – Variables of Importance

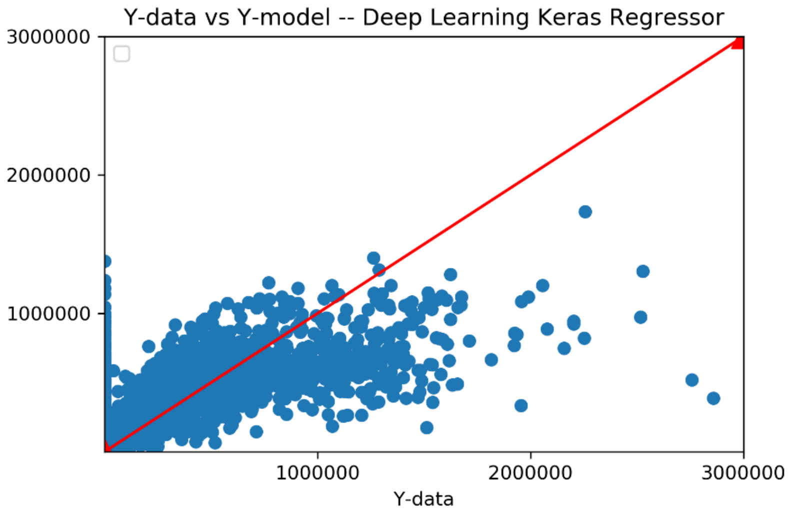




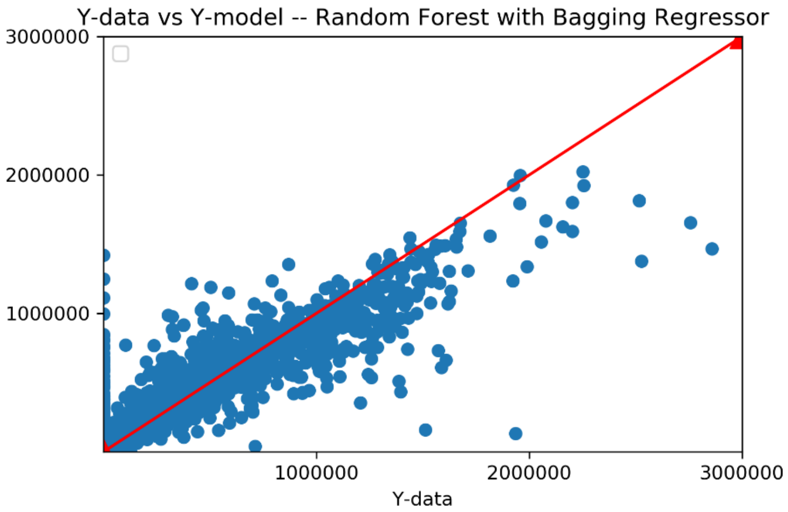
Actual - Header	Short-Header
api10	API
bottomHoleTemp	BHT
bottomHoleTempDepth	BHTD
chokeSize	CS
cum3MonthsBoe	c3mB
cum3MonthsWater	c3mW
cum6MonthsBoe	c6mB
cum6MonthsWater	c6mW
cum12MonthsBoe	c12mB
cum12MonthsWater	c12mW
cum24MonthsBoe	c24mB
cum24MonthsWater	c24mW
cum60MonthsBoe	cTotB
cum60MonthsWater	cTotG
cumTotalOil	cTotO
cumTotalWater	cTotW
cumulativeGasOilRatio	cGOR
EURBoe	EURB
first3MonthsGasOilRatio	3mGOR
firstGasOilRatio	fGOR
gasGravity	SpGr
lateralLength	LL

oilGravity	Ogr
perfInterval	pL
praclPGasOilRatio	IpGOR
proppantConcentrationLbsPerBbl	pConc
proppantLbsPerFoot	pBft
proppantMeshSize	pMs
proppantType	pT
simulFrac	sF
totalDepth	TD
totalFluidBbls	TF
totalProppantLbs	TPr
treatmentType	Ttype
tvd	TVD
peak3monCumulativeGas	p3mCg
peak3monCumulativeOil	p3mCo
peak6monCumulativeGas	p6mCg
peak6monCumulativeOil	p6mCo
peak12monCumulativeGas	p12mCg
peak12monCumulativeOil	p12mCo

Results – DL (unoptimized) vs SL



Deep Learning – Keras Regressor

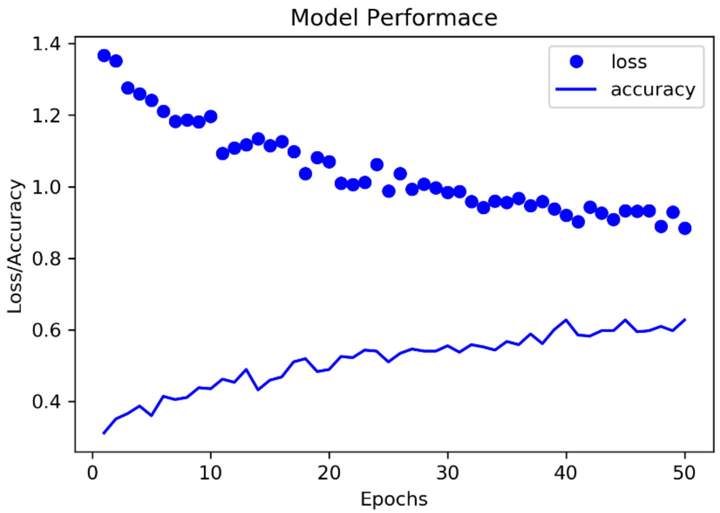


Random Forrest -- Bagging

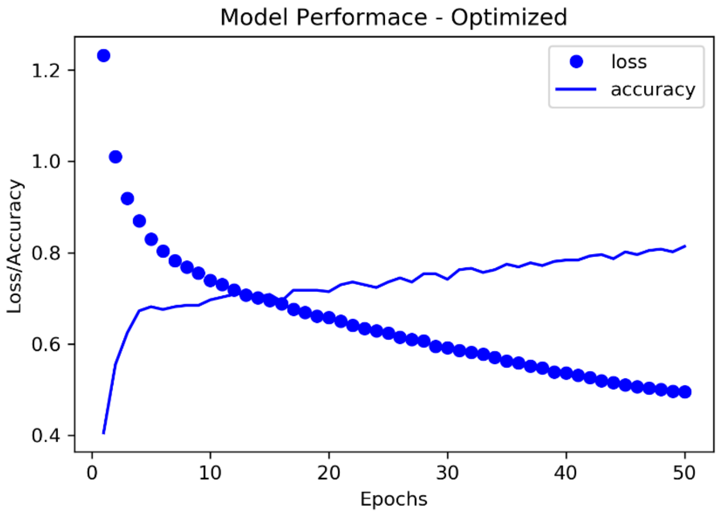
Deep Learning Optimizing – Hyper Parameter Search

Parameter Name	Parameter Values
Activation	Softmax, softplus, softsign, relu, tanh, sigmoid, hard sigmoid, linear
Dropout	Dropout rate, weight constraint
Init mode	'uniform', 'lecun_uniform', 'normal', 'zero', 'glorot_normal', 'glorot_uniform', 'he_normal', 'he_uniform'
Learning Rate	Learning rate, momentum, rho
Neurons	Number of neurons
Optimizer	'SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Adamax', 'Nadam'

Deep Learning – How good is Optimization



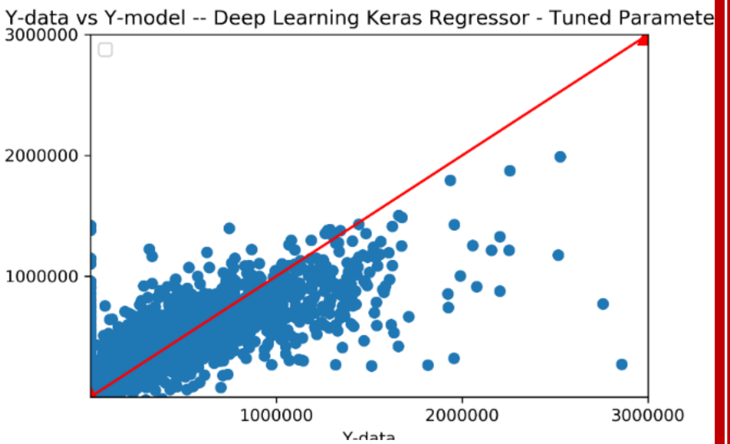
Model Performance

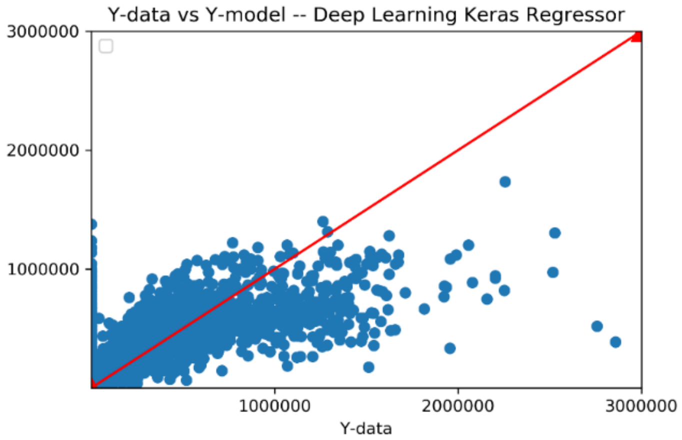


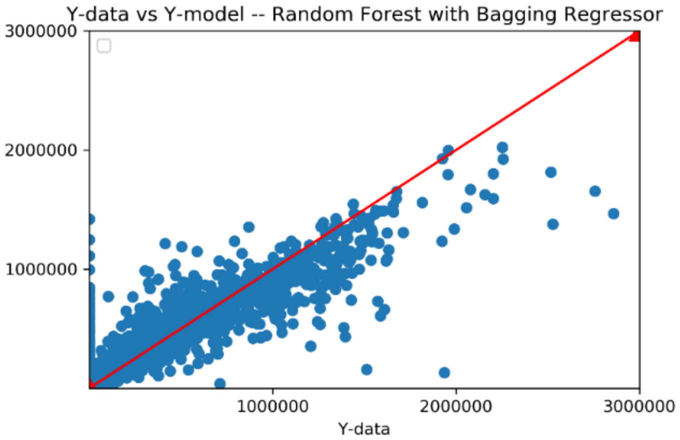
Model Performance - Optimized

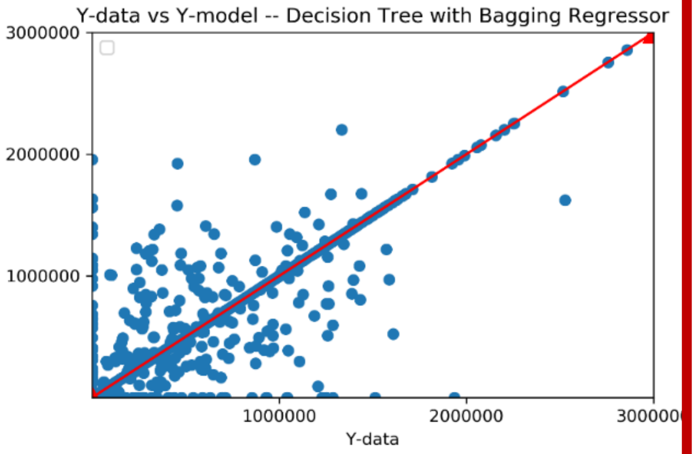
Results – DL (Opt) vs SL

DL









SL

Case Study II

Using LSTM to Forecast Decline Curves - EagleFord Dataset

Methodology

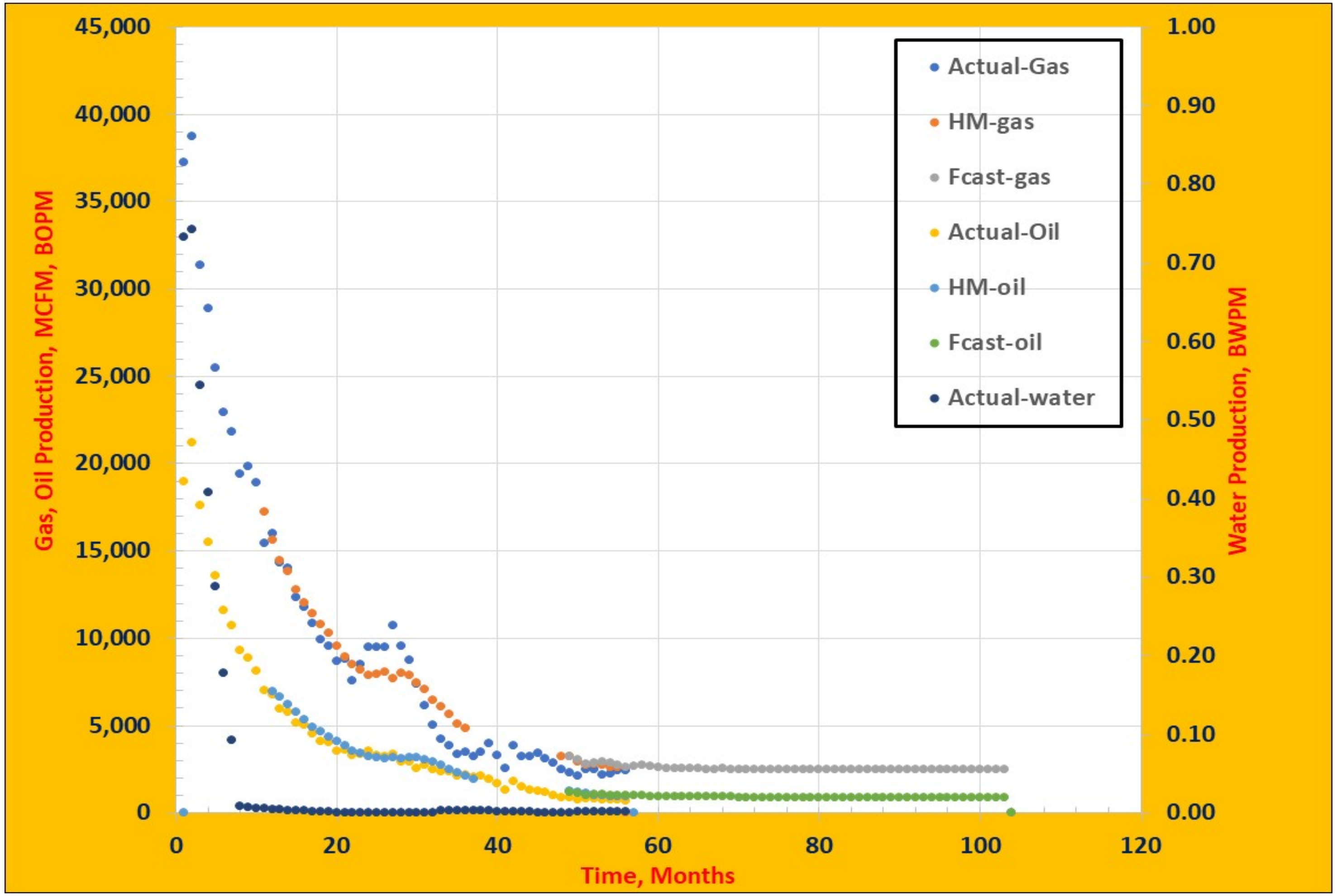
- Specialized Deep Learning Technique – Long-Short Term Memory (LSTIM)
- The difference is it has memory and therefore good for time series data e.g. weather forecast, sales forecast, decline curves etc.
- LSTM is specialized form of RNN to process sequence data and output a sequence data
- Types of LSTM – Vanilla, Stacked, BiDirectional, CNN-LSTM
- Case Study II – Three Phase Production Forecast of an Eagle Ford Horizontal Well

LSTM – 3 Phase Production HM & Forecast

- 55 months of production
- 2/3rd to HM, 1/3rd to hind cast
- All three phase production forecast
- *n_step* is the key parameter: number of past time steps used to forecast next step

Results sensitive to *n_step*

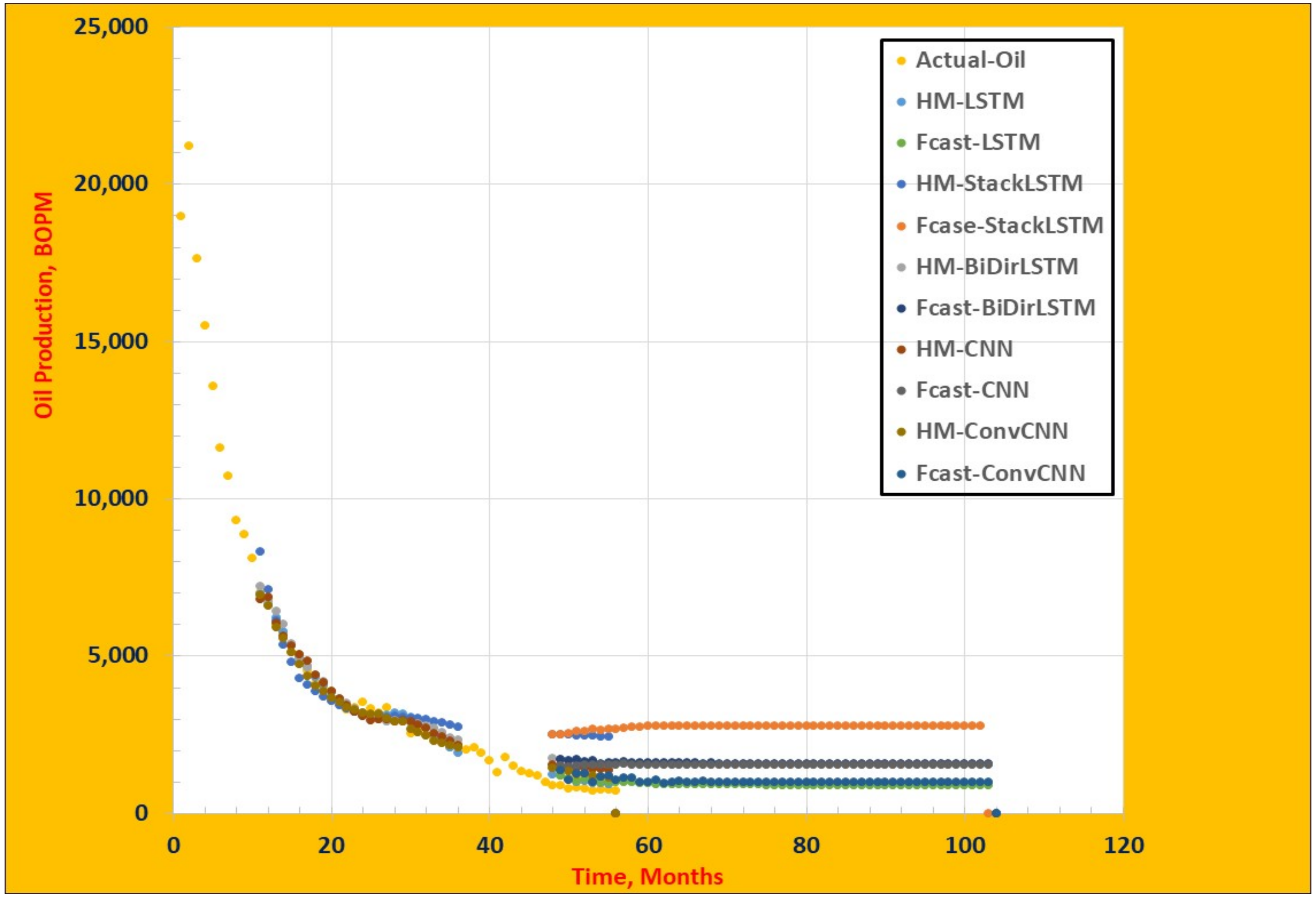
Adjoining figure *n_step* = 10



Sensitivities to Variants of LSTM

- Sensitive to type of LSTM

Adjoining figure *n_step* = 10



Summary and Conclusions

- Systematic approach to applying SL and DL methods are elaborated. The workflow consists of data prep, exploratory data analysis, model selection, model validation, model parameter tuning, selection of variable of importance, model application.
- SL (RF, DT, MLP with and without bagging) and DL methods are applied to a large Delaware basin data set in order to find relationship between the driver variables to predict target variables.
- DL learning methods need parameter optimization to get better results. RF with bagging seems to outperform others.
- Feasibility of LSTM and its variants is investigated to HM and forecast a representative Eagle Ford well production. Although all methods perform good in HM data set but forecast performances differ. Therefore, parameter tuning is needed for better results.