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Data Analytics and Machine Learning in Reservoir Analysis

Roland N. Horne
Stanford University

Society of Petroleum Engineers
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Big Data in Our Daily Lives

- Personalized marketing
- GPS and traffic monitoring
- Self-driving cars
- Customer service
- Character recognition
- Speech recognition
- Translation
- Reservoir engineering!

Machine Translation

- Computer-based translation has been the target of Computer Science since the 1950s.
- Rule-based methods had rather limited success.
  - *"The spirit is willing, but the flesh is weak."*
  - *"The vodka is OK, but the meat is terrible."*

  (Matthew 26:41)

- Modern-day methods based on machine-learning and big data are now practical and useful tools.
  - Google Translate, Bing Translate, etc.

Machine Translation

- Well monitoring can provide a continuous record of flow rate and pressure, which gives us rich information about the reservoir and makes well data a valuable source for reservoir analysis. Recently, it has been shown that machine learning is a promising tool to interpret well transient data. Such methods can be used to denoise and deconvolve the pressure signal efficiently and recover the full reservoir behavior. The machine learning framework has also been extended to multiwell testing and flow rate reconstruction.

- 井监测可以提供连续的流速和压力记录，为我们提供有关油藏的丰富信息，并使井数据成为油藏分析的宝贵资源。最近，已经表明机器学习是解释良好瞬态数据的有前途的工具。这些方法可用于有效地对压力信号进行去噪和去卷积并恢复完整的储层行为。机器学习框架也已扩展到多井测试和流量重建。

Chinese

Self-Driving Cars (2005)

- Stanley won the 2005 Desert Challenge by using AI and data analytics in place of rule-based navigation.

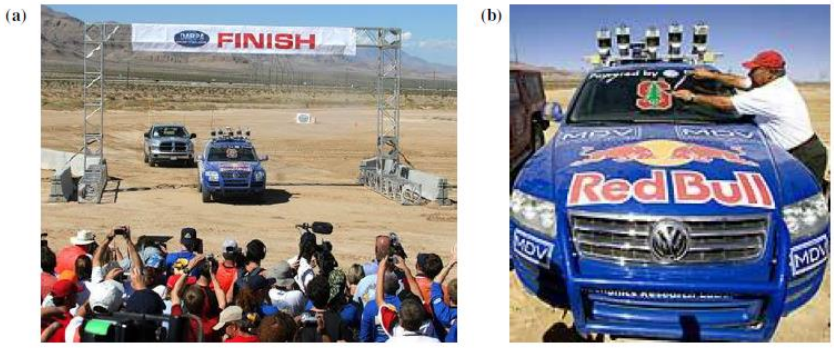
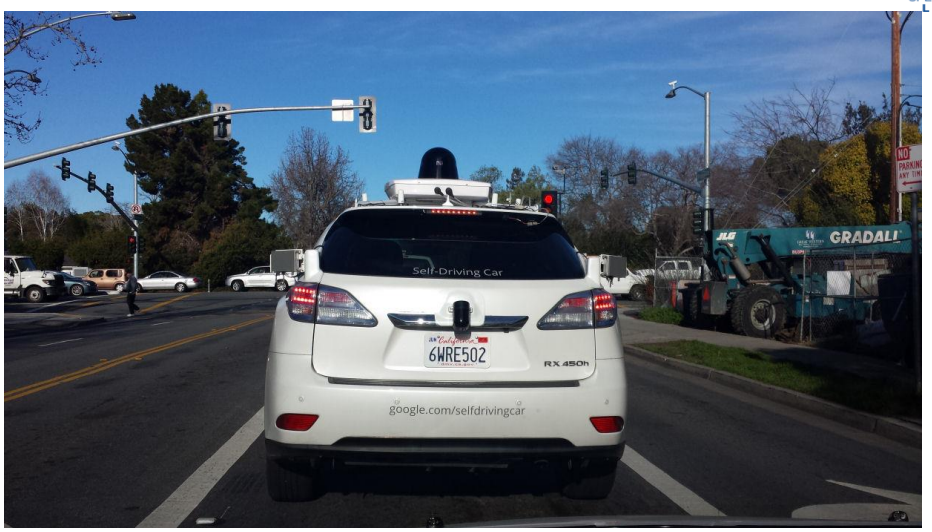


Figure 1: (a) At approximately 1:40pm on Oct 8, 2005, Stanley is the first robot to complete the DARPA Grand Challenge. (b) The robot is being honored by DARPA Director Dr. Tony Tether.

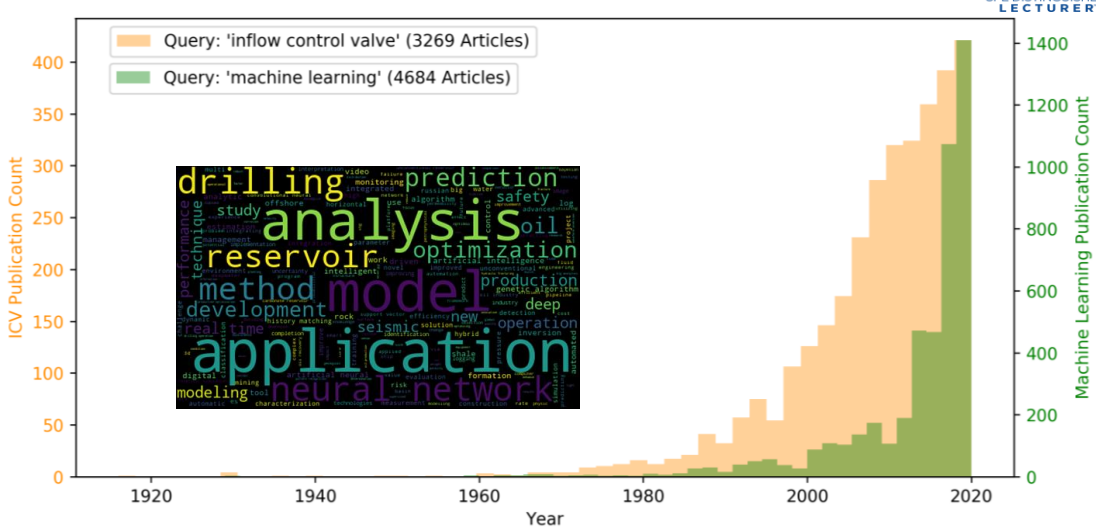
Thrun et al. (2006)

Self-Driving Cars (2016)



Self-Driving Cars

Scraping from OnePetro by Jabs Aljubran



SPE-196003-MS (2019) Aljubran & Horne, Prediction of Multilateral Inflow Control Valve Flow Performance Using Machine Learning

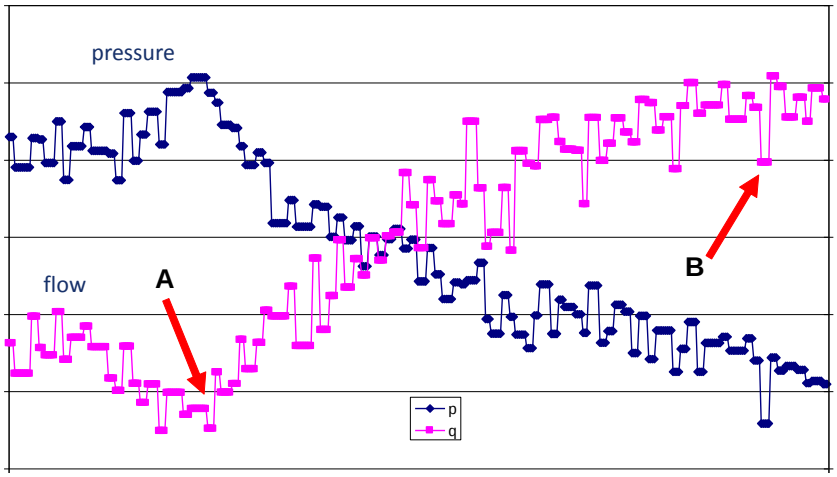
Today's Talk

- Applications:
  1. Permanent downhole gauges
  2. Flow monitoring
  3. Well alerts
- Methods:
  - Artificial neural networks (ANN)
  - Feature-based machine learning
  - Kernel-based methods
  - Convolution
  - Nonparametric regression

1. Permanent Downhole Gauges

- More than 20,000 installed worldwide.
- Usually installed to monitor downhole equipment.
- Data rarely applied for reservoir analysis.

Not All "Noise" is Noise



A – flow event B – noise event

Machine Learning

Applications

- Online product recommendations
- Google brain
- Google Translate

Basic idea

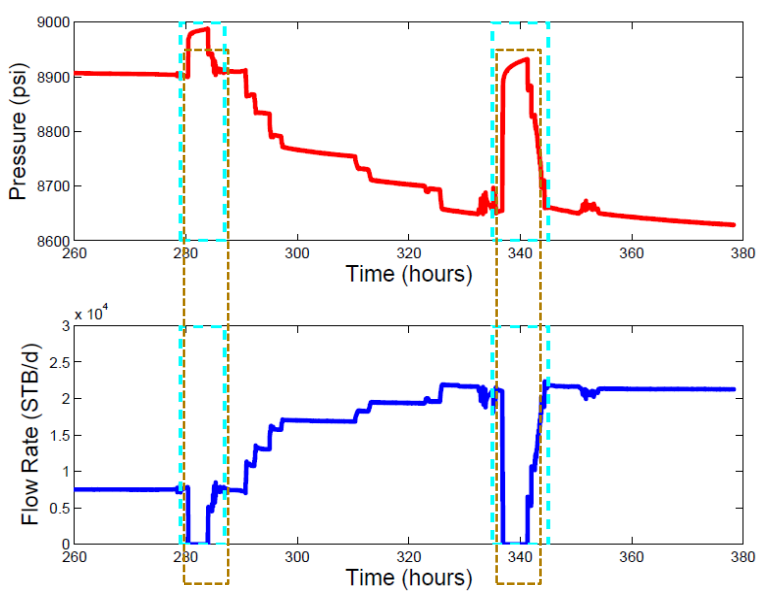
- Explore the patterns (correlation between p-q-T) behind the data (PDG data)

Workflow

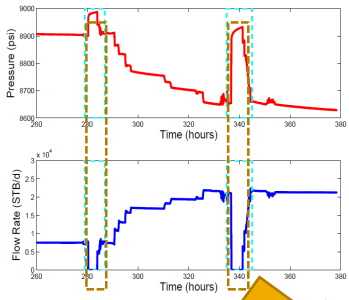
- Acquire training data
- Train algorithm to learn parameters
- Input test data and use trained parameters for prediction

Neural network trained from still frames from unlabeled YouTube videos, learned to detect cats (Google, 2012)

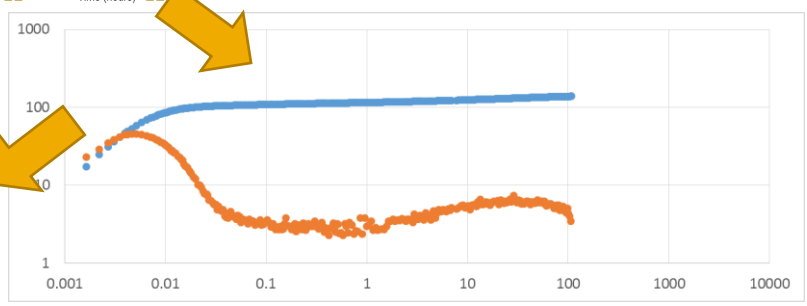
Conventional Well Test Interpretation



Conventional Well Test Interpretation

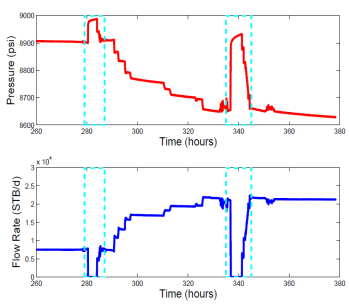


Analyze just the buildups
100 hours of data out of
a record 10,000 hours long



k, s, C

Machine Learning Based Well Test Interpretation



train

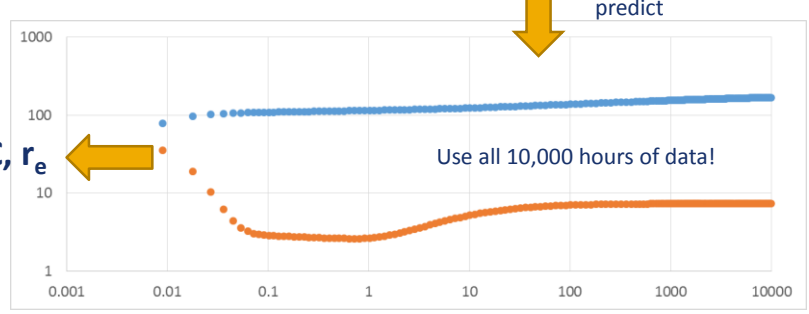
Constant flow rate

input

Machine learning model

$$p = f(q, t)$$

predict

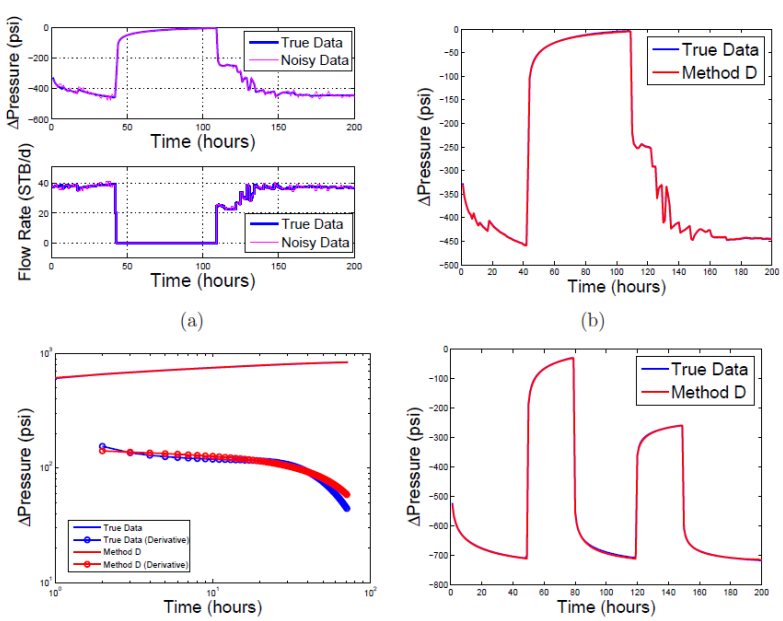


k, s, C, r_e

Advantages of Machine Learning

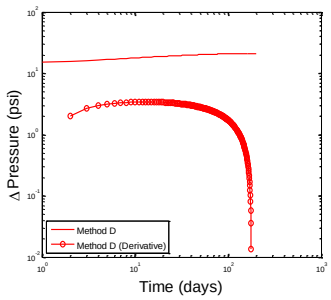
- Measurements were obtained and stored, but not used as much as they could be.
- Hidden in the PDG data, there should be some useful information that could help to better describe the reservoir.
- Utilize the <u>whole</u> *noisy* data set to make interpretation.
- Reservoir model can be revealed without knowing it in advance.

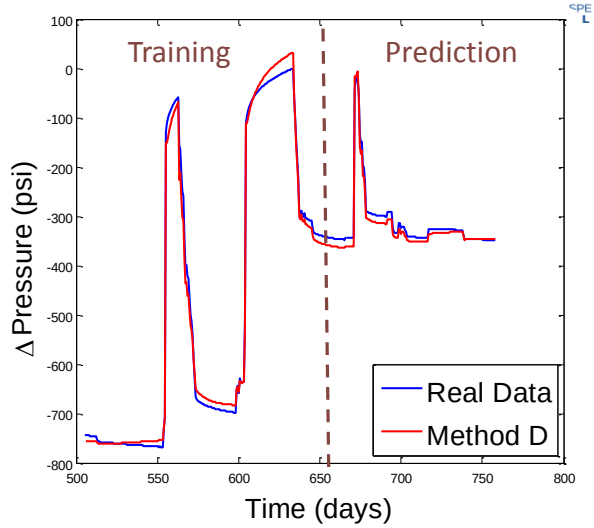
Pressure-Flow Interpretation



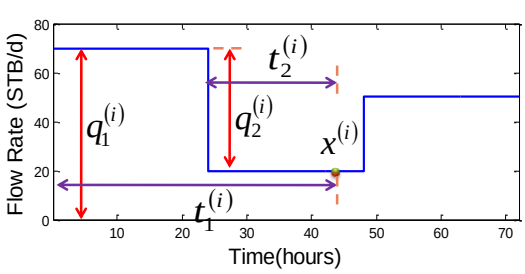
p-q interpretation using convolution kernel approach (Liu & Horne, SPE-166440)

Real Case: Cross Validation





Feature-Based Learning



k^{th} flow rate change

$$\mathbf{x}_k^{(i)} = \begin{pmatrix} q_k^{(i)} \\ q_k^{(i)} \log t_k^{(i)} \\ q_k^{(i)} t_k^{(i)} \\ q_k^{(i)} / t_k^{(i)} \end{pmatrix}$$

Time elapsed from k^{th} flow rate change

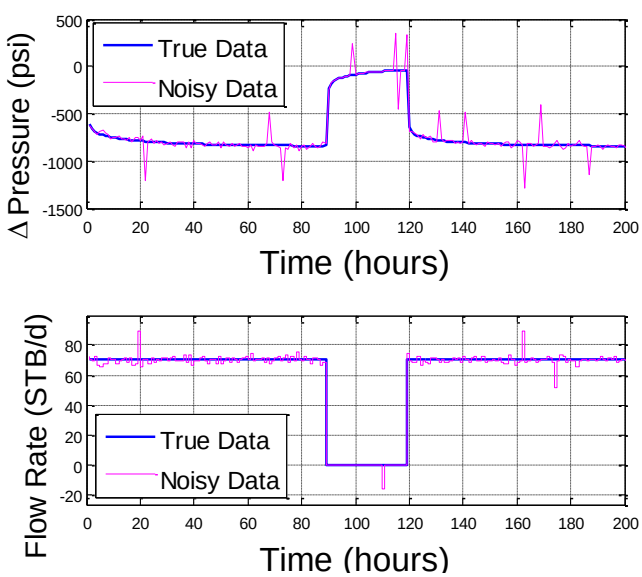
A basket full of physics!

How About Noisy Data?

- Outliers
- Aberrant segments

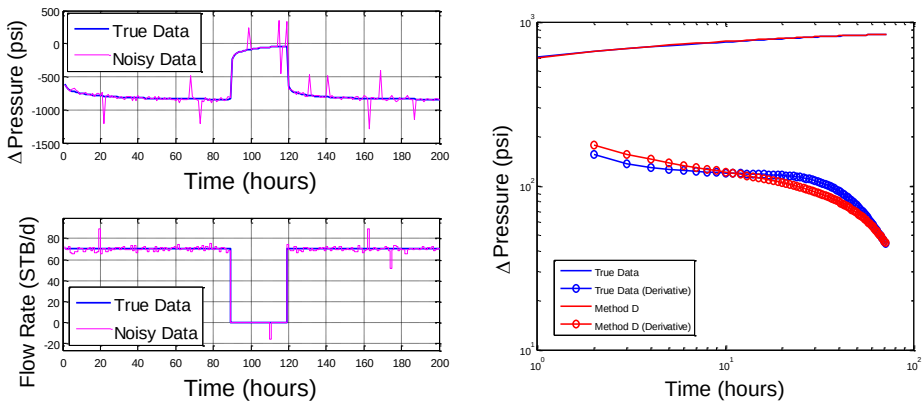
- Death to Deconvolution!

Outliers



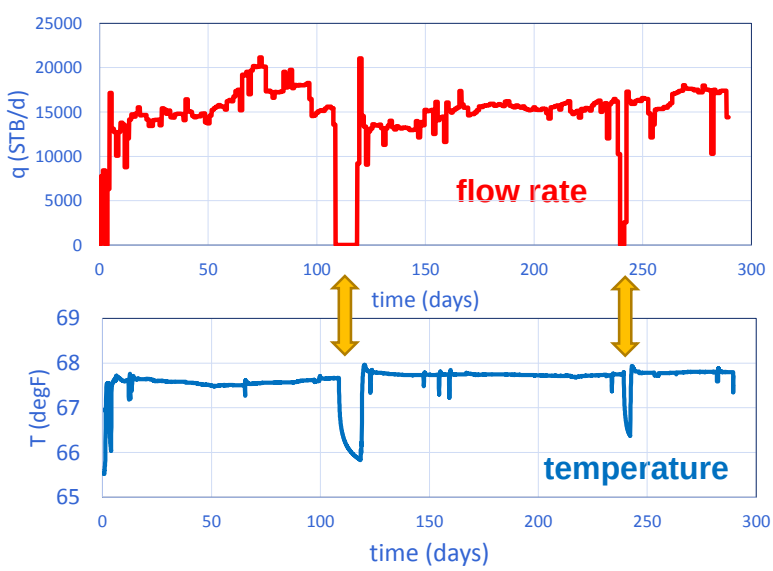
6% of pressure and 3% of flow rate training data are outliers; 3% artificial normal noise everywhere.

Outliers

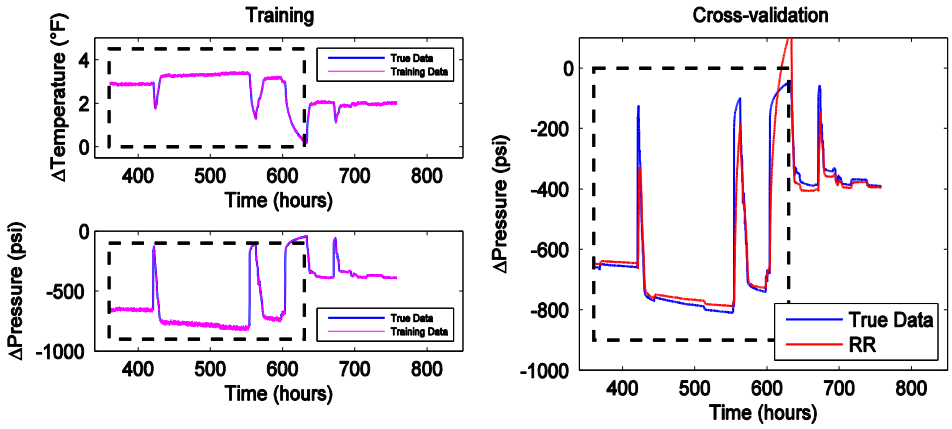


6% of pressure and 3% of flow rate training data are outliers; 3% artificial normal noise everywhere.

Temperature Data

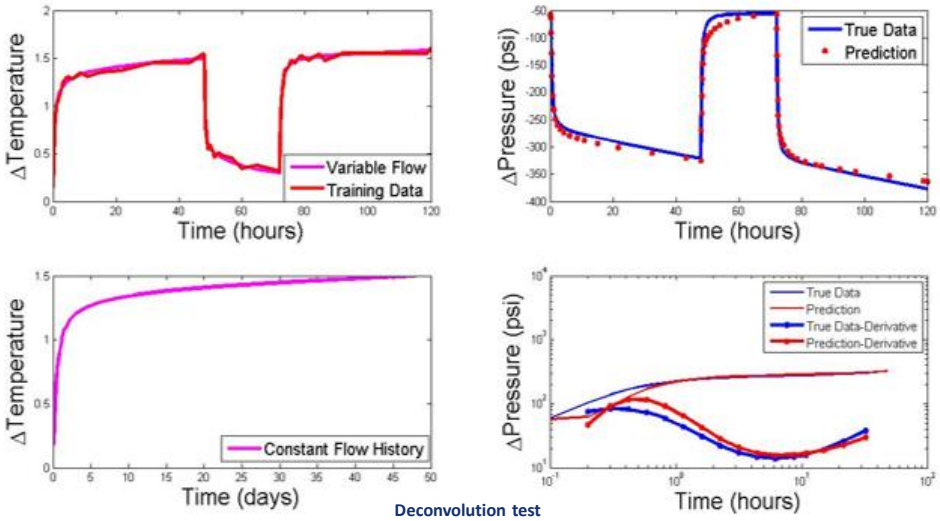


Model from T to p
Pressure History Reconstruction



SPE174034 • Appling Machine Learning Techniques to Interpret Flow Rate, Pressure and Temperature Data From Permanent Downhole Gauges • Chuan Tian

Model from T to p
Temperature as a Flow Rate Substitute



Deconvolution test

2. Flow Rate Reconstruction

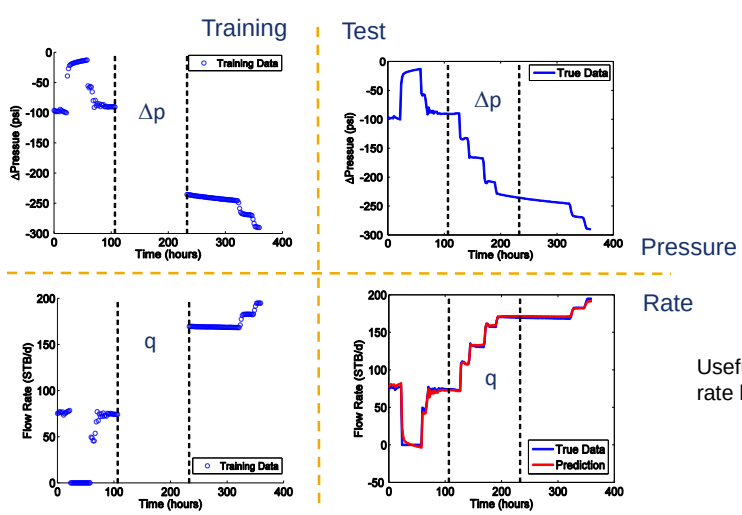
- Idea
  - Machine learning cares about the patterns, not sensitive to the modeling direction

$$\boldsymbol{p = p(q,t)} \text{ to } \boldsymbol{q = q(p,t)}$$

- Feature

$$x^{(i)} = \begin{bmatrix} \sum_{j=1}^{i}\left(p^{(j)} - p^{(j-1)}\right) \\ \sum_{j=1}^{i}\left(p^{(j)} - p^{(j-1)}\right) log\left(t^{(i)} - t^{(j)}\right) \\ \sum_{j=1}^{i}\left(p^{(j)} - p^{(j-1)}\right)\left(t^{(i)} - t^{(j)}\right) \end{bmatrix}, i = 1, \dots, n$$

Missing Field Data



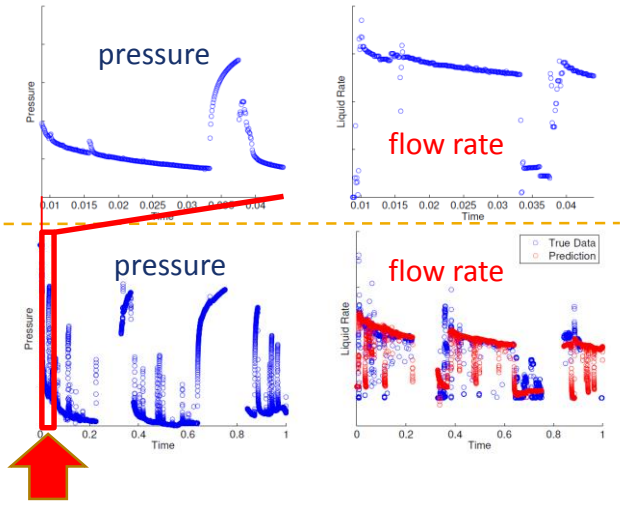
Useful when part of rate history is missing

Practical Application 1: Flow Rate Reconstruction

- Separator that measured flowrate
- Discontinuous flowrate (zeros) because the well was not always aligned to the separator

Train on a short period when flow rate was measured

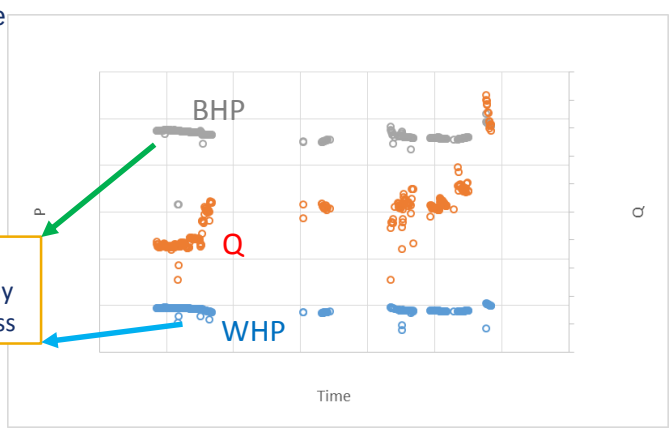
Time scale of test data 30x that of training data



3. Wellbore Modeling

- 309 daily averaged measurements during a period of nearly 3 years
- WHP: wellhead pressure
- DHP: downhole pressure
- Q: surface flow rate

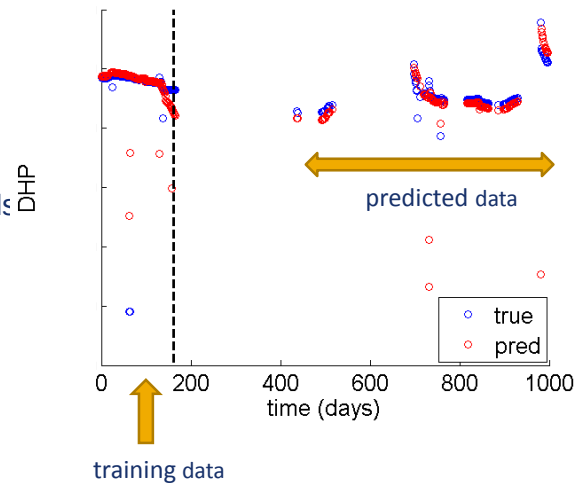
WHP and DHP are strongly correlated by wellbore pressure loss



Practical Application 2: Model DHP Using WHP

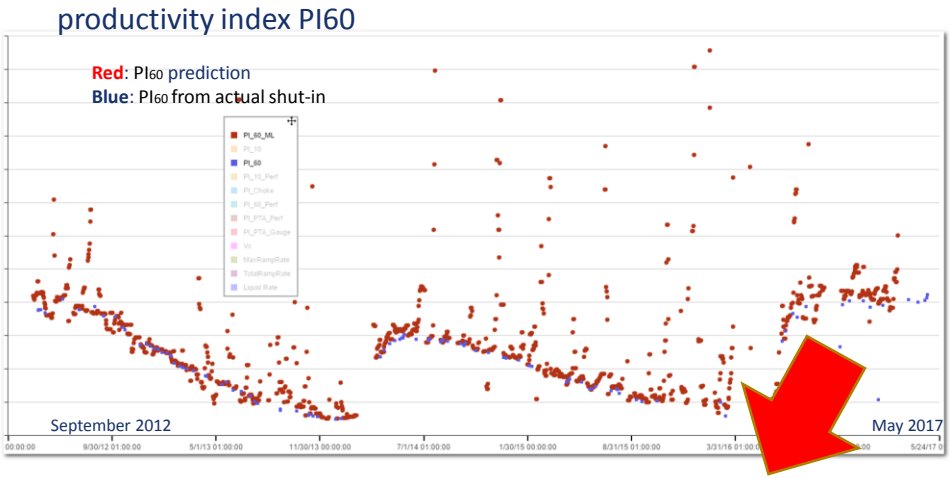
- Input = WHP
- Target = DHP
- Lasso method

- Useful if the PDG fails
- Useful as "well alert"



Practical Application 3: Productivity Estimation

- Train on q-p data → virtual shut-in → predict BHP → well productivity index PI60



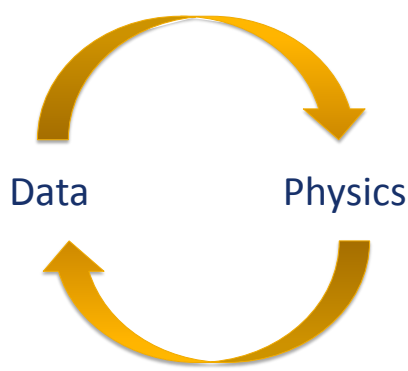
Machine learning based productivity index calculation offsets need for shut-ins

(Sankaran et al., 2017. SPE-187222)

Overall

1. Permanent downhole gauges (PDG) **[q ➔ p]**
   - Reveal the underlying reservoir model, *robust against noise, outliers and aberrations*!
   - Can use temperature data to add information and/or to substitute flow rate data.
2. Flow monitoring **[p ➔ q]**
   - Can fill the unrecorded gaps in flow rate records.
   - Can allocate flow well-by-well based on manifold record.
   - Testing without shut-in!
3. Wellbore modeling **[WHP ➔ DHP]**
   - Discovery of relationship between downhole and surface conditions can provide missing data or alert out of pattern events.

Final Thought



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whakawhetai koe! terima kasih! Je vous remercie! Teşekkür ederim!

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